ADAPTIVE DECISION SUPPORT SYSTEM TO NAVIGATE THE COMPLEXITY OF POST-DISASTER DEBRIS MANAGEMENT

by

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A Dissertation

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Doctor of Philosophy

Lyles School of Civil Engineering

West Lafayette, Indiana

December 2019

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미국에서 함께 공부하면서, 학문적인 지식을 교류했던 모든 동료들 그리고 친구들에게 한없는 감사함을 전하며

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my academic adviser, Dr. Makarand Hastak, for his valuable and patient guidance, and enthusiastic encouragement for my academic research and professional career development at Purdue University. His academic insights and fruitful research experiences in multiple fields enable me to learn various research methodologies and develop a theoretical framework that becomes the backbone of my research framework.

I would also like to express my deep gratitude to my PhD committee members, Dr. Suresh Rao, Dr. Walter Ammann and Dr. Andrew Whelton, who willingly shared sagacity and precious time with patience and sincerity about my research and dissertation. From numerous discussions on the research methodologies and framework, I was able to improve a methodological framework and have a better knowledge of complex system modeling and simulations.

Last but not least, my sincere gratitude and love go to my parents, Youngmoon Kim and Moonja Hong, for their endless love and lifelong support during my academic journey in the United States. It enables me to obtain my PhD degree at Purdue University and start a new journey to continue my professional career development. In addition, I would like to express my love to my brother, Taeyoon Kim and his wife, Minjung Kim. Unfortunately, I haven't met their children, Chan Young and Chan Jin, yet, but wish to see you them very soon. I would like to thank my girlfriend, Byoungha Lee, for being with me during this academic journey at West Lafayette, Pittsburgh, and Oklahoma City. I wish it becomes a part of our beautiful memories. Lastly, I would like to thank Keunwoo Chen and Keumran Lee and the other members in BaMI, Purdue CEM faculty and staff, and SPARC members.

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LIST OF ABBREVIATIONS

Abbreviation	Full name	Notes
ABM	Agent-Based Model	
CBR	City of Baton Rouge	
CRED	Centre for Research on the Epidemiology of Disasters	
CY	Cubic Yard	1 cubic yard = 27 cubic feet
DHS	U.S. Department of Homeland Security	
DSS	Decision Support System	
EM-DAT	Emergency Events Database	
FEMA	U.S. Federal Emergency Management Agency	
GIS	Geographic Information System	
LDEQ	Louisiana Department of Environmental Quality	
SoS	System-of-Systems	
TDMS	Temporary Debris Management Site	
U.S. EPA	U.S. Environmental Protection Agency	
UNEP	United Nations Environment Programme	
UNISDR	United Nations Office for Disaster Risk Reduction	

ABSTRACT

Disaster debris management is critical to the success of disaster recovery systems. While there are multiple disaster mitigation strategies and post-disaster debris management plans, it is hard to implement because of: (i) the uniqueness of disaster incidents and randomness of its impacts; (ii) complexity of disaster debris removal operations, policy and regulations and (iii) interdependency of multiple infrastructure networks. Also, delayed debris removal operation affects following emergency response activities. Furthermore, uncontrolled debris removal activities can result in significant environmental and public health consequences. Therefore, there is a need for a systematic approach to optimizing post-disaster debris management systems.

This research is aimed to understand the complexity of debris management and associated emergent dynamics through the lens of an adaptive system-of-systems (SoS). To develop the adaptive decision support system, this research (a) identifies the interdependent infrastructure network within a community and its relative importance; (b) develops real-time GIS database to integrate the data associated with critical infrastructure and geographical characteristics in the community map; (c) designs and selects a TDMS network to analyze the required number, capacity and resources, based on engineering-technical, managerial, and social-political dynamics; (d) simulate the productivity of debris-management SoS based on the real-time GIS database to gain insight into the impact of the dynamical nature of a disaster-affected area; and (e) develop a visualized interactive GIS-based platform for debris management to communicate real-time debris clearance strategies and operations among different agencies and organizations.

To evaluate the proposed framework and decision support system, this research conducted a case study, debris removal operation in the city of Baton Rouge, after the 2016 Louisiana flood. The results demonstrated the influence of sub-systems such as TDMS locations and capacity, road network condition, available resources, existing regulations and policies, characteristics of community on the behavior of the entire disaster debris removal management as a whole.

The proposed decision support system for effective disaster debris management will be beneficial for emergency agencies and disaster-prone communities to evaluate and optimize their disaster

debris management system. Also, the system can be systematically integrated with other emergency response systems to maximize the efficiency of the entire disaster responses during post-disaster situations.

CHAPTER 1. INTRODUCTION

1.1 Introduction

Over the last twenty years, the majority (90%) of natural disasters have been caused by weather-related events such as floods, storms, earthquakes, and heatwaves (UNISDR and CRED 2015). EM-DAT (CRED's emergency events database) recorded 6,557 weather-related disasters worldwide: natural disasters claimed 606,000 lives (i.e., average of some 30,000 annually) with around 4.1 billion people injured, left homeless, or in need of emergency aid. According to UNISDR's report, China has the highest number of natural disasters, 286, from 2005 to 2014 (UNISDR 2017) (see Figure 1-1). Interestingly, the U.S. has incurred the most economic damage ($443 billion). Similarly, there were less number of natural disasters in Japan, but their economic looses from the disasters are as significant as that of China, $ 239 vs. $ 265 billion.

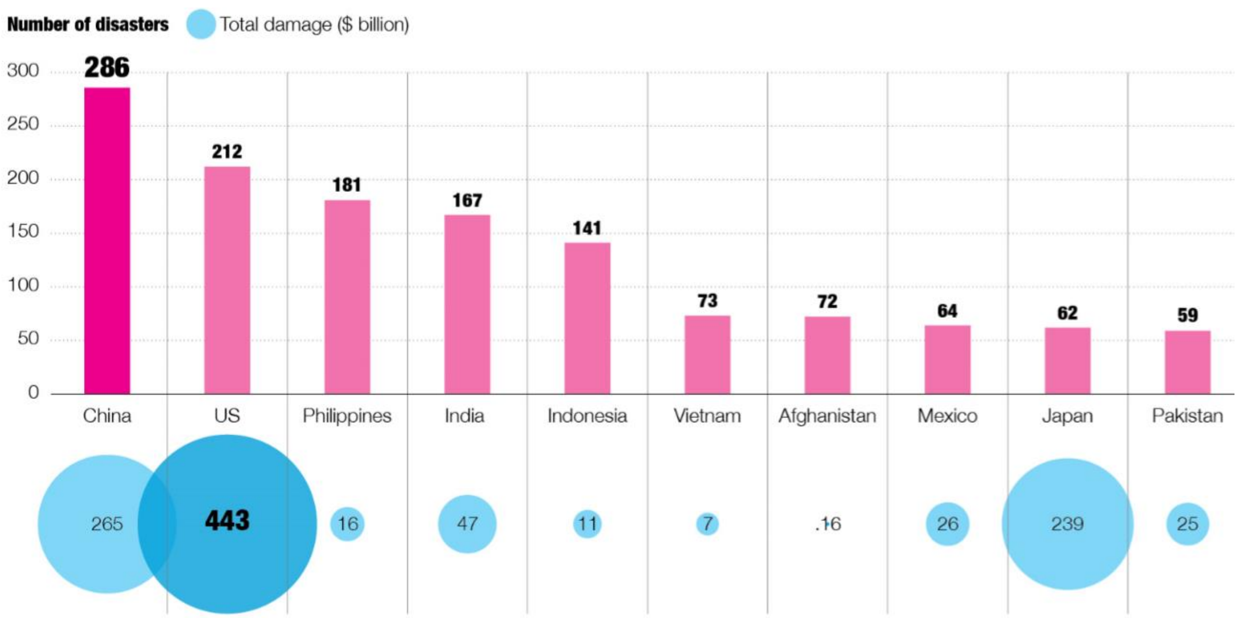


Figure 1-1 Top 10 countries with most disasters, 2005 – 2014

Note: China has the highest number of disasters from 2005-2014, but the US has incurred the most economic damages, and while Japan is far behind in the number of disasters, its economic loss is as significant as that of China (image from UNISDR 2017).

Economic losses from disasters are increasing every year. The estimated economic losses ($ 153.9 billion) in 2016 were the fourth-highest since 2006 (i.e., almost 12% above the annual 2006-2015 damages average, $ 137.6 billion) (Guha-sapir et al. 2011): This increase in total costs is partially related to the $ 59 billion damages coming from hydrological disasters. Another part of this increase is attributable to the $ 16 billion damages caused by weather-related disasters, which corresponds to 1.69 times the annual average. For example, the wildfire in Canada made US$ 4 billion damages while one drought in China cost $ 3 billion. The 2016 economic losses from meteorological disasters ($ 46.6 billion) remained close to the 2006-2015 annual average ($ 48.4 billion). However, damages from geophysical disasters ($ 32.8 billion - this is mainly influenced by 2011 tsunami in Japan) appeared below their annual average ($ 46.1 billion). When removed from the average, the 2016 costs from geophysical disasters are, then ,30.6% above the revalued average ($ 25.1 billion).

Disasters in the U.S.

In 2017, there were 16 weather-related disasters across the U.S., including Hurricane Harvey, Irma, and Maria: the economic losses exceeded $1 billion each. Disaster recovery costs exceeded $300 billion in 2017 (NOAA 2018).

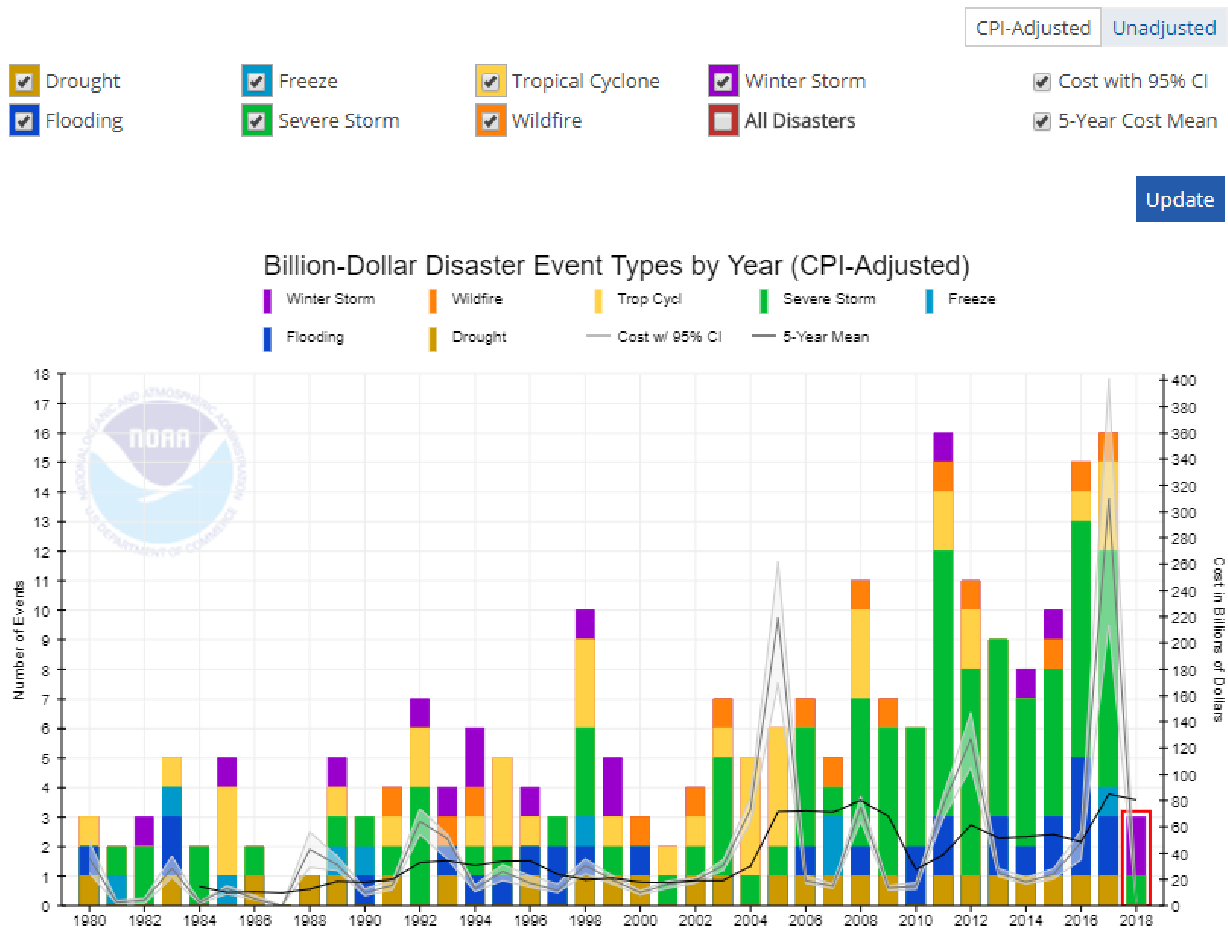


Figure 1-2 Type and number of disasters in the U.S.

Note: 95% confidence interval (CI) probability is a representation of the uncertainty associated with the disaster cost estimates. Monte Carlo simulations were conducted to generate the upper and lower bounds under the given uncertainty. The number of events in 2018 was updated on April 6, 2018 (NOAA 2018).

Debris includes wasted soils and sediments, vegetation (e.g., trees, limbs, shrubs), construction and demolition debris (e.g., entire residential structures and their contents), vehicles, food waste, white goods (e.g., refrigerators, freezers, air conditioners), household hazardous waste (e.g., cleaning agents, pesticides, pool chemicals), and municipal solid waste (e.g., standard household garbage, personal belongings) (FEMA 2007; Oregon Department of Environmental Quality 2011; U.S. EPA 2008). Sometimes, disasters results in the generation of mixed debris that increases the complexity of seperation, tranportation and disposal processes (Roper 2008). The objectives of debris management are slight different in short- and long-term period. In the short term, rapid debris clearance on road network is critical for emergency responses including medical, shelter and food services. For a long-term perspective, appropriate debris management methods are required to prevent any environmental issues or contamination from piles of debris or debris in temporary sites (Luther 2010).

Debris in the residential area

Photo by J.T. Blatty/FEMA

Debris accumulated on the curbside

Photo by Laura Guzman/FEMA

Piles of mixed debris on the curbside

Photo by J.T. Blatty/FEMA

Piles of debris line near the shopping centers after a week of flood

Photo by J.T. Blatty/FEMA

Reference: (Blatty 2016; FEMA 2016a)

Figure 1-3 Debris generated after the 2016 Louisiana flood

Debris management is the first process during disaster recovery

While debris management is one of many competing priorities for emergency agencies, it has been often overlooked (US EPA 2017a). Disaster debris should be systematically managed to 1) protect human health from any environmental contaminations from a pile of debris, and 2) save existing capacity of landfills or other waste-related facilities by minimizing direct debris input from an disaster-affected community for future generations. Thus, it involves advanced planning and operation management to systematically coordinate collaborations among individuals/groups/parties at different levels of state- and local municipals as well as private sector with experience and expertise in debris and solid waste management.

A huge amount of debris generated a disaster easily hampers emergency responses, recovery and reconstruction phases. The amount of debris is sometimes similar to 5 ~ 10 times of the annual solid waste generation (see in Table 1-1). For example, the 2015 Nepal earthquake generated around 4 million tons of debris in Kathmandu valley, and it was almost 11 times higher than the annual solid waste (Bogaty 2015).

Table 1-1 Amount of debris generated by disasters

Year	Event	Volume/Weight	Data
2017	Hurricane Harvey, Texas, USA	8 million CY	(CBS 2017)
2016	Louisiana Flood (East Baton Rouge)	1.3 million CY	(Gallo 2016)
2015	Earthquake, Nepal	10 million tons*	(Singh 2015)
2012	Hurricane Sandy, USA	5.25 million CY	(FEMA 2013)
2010	Earthquake, Haiti	23~60 million CY	(Booth 2010)
2005	Hurricane Katrina, USA	76 million CY	(Luther 2006)

** This study used the reported units rather than converting it to CY to tons, or, tons to CY, as the exact types of debris were not included in the reports.*

After the 2016 Louisiana flood, 1.4 million CY of debris was generated in the city of Baton Rouge. According to the Louisiana annual solid waste report, estimated annual solid waste in East Baton Rouge was about 502,994 CY/year (see Table 1-2). Thus, the 1.4 million CY of debris was about three times higher than the amount of the annual solid waste generation.

Table 1-2 Municipal solid waste landfill in East Baton Rouge

Name	Remaining capacity (cubic yards)	Remaining capacity (months)
East Baton Rouge Parish North Landfill	18,317,400 CY	437 months

Reference: (LEDQ 2015)

Debris management should be carefully calibrated for each debris removal operation because of 1) the uniqueness of incidents and 2) randomness of impacts associated with low-probability and high-consequence events (Altay and Green 2006; Cutter et al. 2010; Kunreuther et al. 2013). In the 2010 Haiti earthquake, the debris generated from the partial destruction of the port blocked certain road segments and it hampered emergency supplies and responses for a couple of months (DesRoches et al. 2011; UNDP 2013).

The *Robert T. Stafford Disaster Relief and Emergency Assistance Act* (i.e., *Public Law 93-288*), stated that state and local governments should develop a disaster mitigation plan for receving certain types of non-emergency disaster assistances (e.g., funding for disaster mitigation project) . It provides the legal basis to state- and local governments for developing their own disaster mitigatin planning (FEMA 2013b). It is also advised that plans for debris management should include detailed strategies for each stage of debris management: debris collection, installment of temporary debris management sites, recycling, disposal, hazardous waste identification/handling, emergency information dissemination to the public, and administrations (U.S. Department of Homeland Security 2011; U.S. EPA 2008).

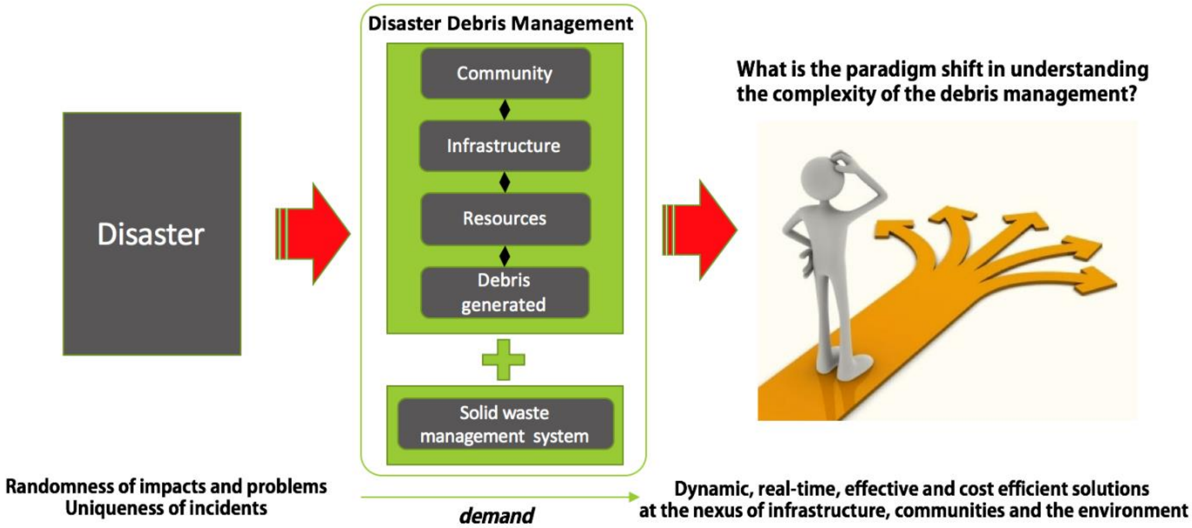


Figure 1-4 Difficulties to understand the complex debris management system

Hills (1998) suggested that disaster management implies a degree of control, which rarely exists in real situations. Altay and Green (2006) agreed that disaster mitigation plans is required before a disaster, but it should have some rooms to adapt unusual challenges created from a catastrophic event. Thus, debris management models should, by their very nature, provide a systematic and flexible approach that is adaptable to a disaster situation and able to expedite debris removal operations (Celik et al. 2015).

1.2 Problem statement

There is a lack of an integrated debris management system to handle the debris generated. Depending on the nature and severity of human-made or natural disasters, and built environments in a community, a disaster can create substantial volumes/types of debris. It can overwhelm the capacity and resources of the existing solid waste management systems and affect multiple following disaster recovery phases. Besides, poorly managed debris can directly affect the entire disaster recovery processes as well as environmental and public health impacts. While the extent and criticality of the impact of debris removal on economic, environmental, and social dimensions of recovery plans, current studies underestimate emergent dynamics of debris management prioritizing its collection or disposal locations, as well as real-time management of resources such as equipment fleets. Thus, it is critical to developing a decision support system integrating the entire debris removal stages such as collection, processing, recycling, and disposal stages.

Also, the effectiveness of disaster debris management depends on not only efficient debris management planning and operation, but also existing capacities and serviceability of critical infrastructure and facilities related to the debris removal after a catastrophic event. Classical reliability theories are widely used to model large complicated systems (Eusgeld et al. 2011). For example, stochastic models such as the Markov and Poisson processes were applied to predict system behaviors under multiple uncertainties. However, these methods/approaches are limited to capture 1) the underlying structure of the system as well as 2) the ability to adapt to failures of subsystems when strong system interdependencies exist. Existing literature and studies in the field of disaster debris management are limited to investigate system efficiency of a debris management component such as type and amount of debris, temporary debris management site, debris transportation, and processing. There is a lack of models to capture the complex interactions in disaster debris removal operations as a complex adaptive system (i.e., a high degree of coupling between the systems). This research clarifies this problem on the specific example, debris management, and then presents the advantages of the system of systems approach with a case study, the 2016 Louisiana flood, and the debris management.

Finally, different agencies lack established channels to communicate debris removal strategies and operation plans as platforms for collaboration to expedite the entire disaster recovery process as well as disaster debris management. The extent and criticality of disaster debris management necessitate an adaptive decision support system, which reflects 1) the unexpected impacts of a disaster, 2) characteristics of the community, its interdependent infrastructure network, and 3) efficient utilization of available resources and infrastructure in real-time.

1.3 Thesis statement

Effective disaster debris management is a crucial component for community resilience from a catastrophic event. Therefore, the thesis of this research is the following:

A new paradigm is required that optimizes the debris management system by analyzing the system behaviors under different planning and operational strategies that effectively adapt both the uncertainty of a catastrophic event and the interdependencies within the components of the debris management system.

Thus, this research proposes a decision support system (DSS) applying an adaptive system of systems approach for effective debris management that considers the uncertainty of a catastrophic event and the interdependency in sub-systems of debris management systems. The DSS can be used to develop, analyze, and communicate mitigation strategies for effective debris management at the interface of community needs, infrastructure performance, and environmental impacts.

1.4 Research objectives

The research objective is to develop an adaptive decision support system (DSS) that can navigate the complexity of post-disaster debris management as well as support optimal decision making after a catastrophic event. The adaptive DSS uncovers emergent characteristics of disaster debris management at the relationship of communities, infrastructure, and the environment. The output would be generalizable: the GIS-based modules in the adaptive DSS can be used to support state- and local decision-makers to identify promising TDMS locations that are robust to uncertainty in disaster characteristics and impacts. This model is calibrated and validated using a case study, debris management in the city of Baton Rouge after the 2016 Louisiana flood, and through agent-based simulation of various adaptive debris management strategies. Specific objectives include:

i. Develop a framework for post-disaster debris management based on the concept of SoS,
ii. Identify a network of interdependent infrastructure systems that influence debris removal within a community and their relative importance,
iii. Develop real-time GIS database to integrate the data associated with 1 and 2 above, and make it available for analysis for the remaining objectives,
iv. Model the selection/design of a TDMS network including (1) geographical characteristics (GIS data) and interdependent infrastructure as identified in 1 and 2 above, (2) availability of resources for debris removal,

v. Simulate the productivity of debris-management on the real-time GIS data to gain insight into the impact of the dynamical nature of a disaster-affected area,

vi. Develop a visual, interactive GIS-based simulation platform for effective coordination among agencies and monitoring on-going debris removal operations under dynamic conditions, and

vii. Establish a feedback loop to incorporate real-time data on debris removal operations in the simulation model for updating corresponding disaster management activities.

1.5 Scope of the research

This research focuses on the development of the adaptive decision support system (through the lens of a complex coupled system) that assists a decision-maker by 1) analyzing complex post-debris management systems, 2) simulating multiple scenarios to understand system behaviors under multiple uncertainties, and 3) identifying optimal solutions given the circumstances/environments after a catastrophic event. The scope of the research includes debris/waste-related management facilities (TDMSs, landfills and recycling facilities), critical infrastructure (physical infrastructure supporting debris (civil, civic, environmental and social), TDMS design and selection model under the consideration of technical, environmental and social performance, the optimal number of resources and the allocations in terms of loaders, hauling trucks and chippers.

To predict the volume and location of debris generated by a disaster, this research used FEMA's Hazus-MH (ver. 4.0.). The types of debris in this study are limited to wood, steel, concrete, and masonry. Other data including road network, built and natural environments, infrastructure was acquired from USGS, city of Baton Rouge, FEMA Hazus-MH, and ArcGIS. The developed research framework and adaptive decision support system are fully scalable to include multi-dimensional system interdependency (temporal and spatial). It can be applied to both natural and man-made disasters in any given circumstance.

1.6 Outline of the dissertation

The main body of this study consists of six chapters. Chapter 1 provides a general overview of this research, including research background and needs, thesis, objectives, and scopes. Chapter 2 reviews extensive literature in the field of disaster debris management, critical infrastructure as well as complex system and simulations. It includes systematic reviews on historical disaster debris management strategies and operations in the U.S., existing debris management plans from FEMA, state- and local-level emergency agencies, numerous subjects related to debris removal including economic, social, and environmental issues. Finally, it illustrates the gap of knowledge and needs for developing an adaptive decision support system for effective post-disaster debris management from a catastrophic event. Chapter 3 illustrates the research approach, framework, methodologies, and expected results. Chapter 4 discusses the development of the adaptive decision support system, including four modules and the detail methodologies applied in each module. Chapter 5 demonstrates an application of the proposed decision support system into a real-world problem using a case study, debris management in the city of Baton Rouge after the 2016 Louisiana flood. Chapter 6 summarizes research conclusions, theoretical and practical contributions, limitations on this research, and future research directions.

CHAPTER 2. LITERATURE REVIEW

The main objective of the literature review is to review and summarize a body of knowledge related to disaster debris management, critical infrastructure and complex system modeling. This chapter establishes existing the gap of knowledge in effective disaster debris management, and support the needs of this research and point of departure.

2.1 Disaster debris management

2.1.1 Phases in disaster debris management

Debris management generally has three phases (Baycan 2004): *emergency response, recovery*, and *rebuild*. Sometimes, each phase is not separate with the other phases. Also the duration of each phase can vary depending on disaster severity and community resiliency.

In an *emergency response phase*, the main priorities of debris removal focus on enhancing emergency responses by cleaning up certain debris on road as well as resulting in public health/safety issues. This phase can go up to between a few days and two weeks (Haas et al. 1977). Recycling efforts on curbside are very limited in this phase (Solid Waste Association of North America 2005).

In the *recovery phase*, the main objectives are to restore critical infrastructure and demolish damaged buildings and houses: The most of debris comes from this phase. The duration of the recovery phase can be affected by numerous decision factors as well as certain circumstances that is out of control from debris management teams. In case of debris removal in Louisiana after 2005 Hurricane Katrina, it took up to five years because of the huge amount of debris (Luther 2006). Sometimes, police investigations at certain areas hamper the access to disaster-affected areas of equipment. Finally, a slow return of residents results in slow debris collection on curbside (Cook, BA 2009).

In the *rebuild phase*, debris is mostly generated from the reconstruction. The duration can be up to 10 years (Haas et al. 1977).

Table 2-1 Three phases and durations in debris management

Emergency	Recovery	Rebuild
Few days ~ two weeks	Up to 5 years	Up to 10 years

US EPA (2017a) suggested that a community should prepare their own debris management plan ahead of any catastrophic event: It will 2) minimize debris removal costs, 3) protect residents from possible public health issues from a pile of mixed debris around a community, and 3) increase the performance of the entire disaster recovery activities including debris cleanup. Thus, a decision-maker must identify the characteristics of community affecting a type of or the amount of debris generated, and develop immediate-, short- and long-term goals to enhance debris removal performance based on the community's needs and existing capacity and resources. However, most of the existing state- and local-level debris management plans are limited to repeat the general debris management plans and guidelines provided from FEMA and US EPA. State- and local municipals should examine their communities including available resources, capacity, and serviceability of waste-related facilities, as well as communication platforms between agencies, contractors and residents.

2.1.2 Characteristic of debris

2.1.2.1 Types of debris

Multiple types of debris are generated based on the characteristics of built environment (e.g., geographic location, population density, and socioeconomic setting) and a type of disasters (U.S. EPA 2008). The variations sometimes require a different debris management approach.

Baycan (2004) classified debris components into three categories:

- *Recyclable*
- *Non-recyclable*
- *Hazardous*

US EPA (2008) categorized debris into five types:

- *Damaged buildings*
- *Sediments*
- *Green waste*
- *Personal property*
- *Ash and charred wood*

FEMA (2007) listed types of debris by a type of disasters (See Table 2-2).

Table 2-2 Typical types of debris by a different type of disaster

	Types of disasters						
	Hurricane	Tsunami	Tornado	Flood	Earthquake	Wildfire	Ice storm
Vegetative	O	O	O	O		O	O
Construction and demolition	O	O	O	O	O		
Personal property/ Household	O	O	O	O	O	O	
Hazardous waste	O	O	O	O			
Household hazardous waste	O	O	O	O	O	O	O
White goods	O	O	O	O	O	O	
Soil and sand	O	O		O	O	O	
Vehicles, vessels	O	O	O	o			

Note: Hazardous materials can enter the debris stream from various sources, including households, commercial activities, and institutional sources, as well as industrial sources.

Reference : (FEMA 2007)

Types of debris in urban areas: A composition of debris generated in urban areas is very similar to that of construction and demolition (C&D). In general, C&D materials consist of the followings:

- *Concrete, asphalt, brick and blocks*
- *Woods in various forms*
- *Metals such as steel and pipes*
- *Frames such as doors, windows*
- *Plumbing components*
- *Insulation materials*
- *Soil and earthen materials*
- *Vegetation*

Types of debris in rural areas: In rural areas, most of debris include natural or organic materials and it may contain a low amount of C&D materials (e.g., synthetic, composite, and metallurgical components).

2.1.2.2 Debris quantities

Debris quantities have been reported in terms of either mass (tons) or volume (cubic yards or meters). However, most of the reports did not include their measurement approaches or methods (e.g., it is hard to identify where and how the volume of debris is measured such as truckloads or landfill volumes) (FEMA 2007).

Table 2-3. Historical disasters and debris quantities

Year	Event	Debris quantity*	Reference
2017	Hurricane Harvey, Texas, USA	8 million CY	(CBS 2017)
2016	Louisiana Flood (East Baton Rouge)	1.3 million CY	(Gallo 2016)
2015	Earthquake, Nepal	10 million tons	Singh (2015)
2012	Hurricane Sandy, USA	5.25 million CY	FEMA (2013)
2011	Japan tsunami	70 - 180 million tons	Yesiller (2012)
2010	Haiti earthquake	23 - 60 million tons	Booth (2010)
2009	L'Aquila, Italy earthquake	1.5 -3 million tons	Di.Coma.C. (2010)
2008	Sichuan, China earthquake	20 million tons	Taylor (2008)
2005	Hurricane Katrina Louisiana USA	99.4 million CY	Luther (2008)
2004	Hurricanes Florida, USA	3.9 million cubic meters	Solid Waste Authority (2004)
2004	Indian Ocean Tsunami	13 million cubic meters	Bjerregaard (2010)
2004	Hurricane Charley, USA	2.6 million cubic meters	MSW (2006)

** Unit for the debris quality is either volume or weight. This study did not convert a unit (e.g., CY to tons, or tons to CY) as the detail types of debris were not reported in the references.*

Estimating debris quantity in a pre- or post-disaster situation is highly recommended to prepare disaster mitigation plans and develop action plans for debris removal operations (EPA 2008). There have been numerous studies/reports that have retrospectively quantified disaster debris. These studies were mainly conducted to improve debris estimation methods and techniques, and support the development of debris management planning and preparedness. This study introduces several debris estimation methods from the literature.

Inoue et al. (2007) studied the specific gravities of the debris generated by the 1995 Great Hanshin-Awaji earthquake. They identified that debris weight in the middle of transportation was generally increased compared to the average weight (see Table 2-4).

Table 2-4 Gravity of debris

Average gravity	**Increased gravity (In the middle of transportation)**
0.59 ton/m3	0.73 ton/m3

Hirayama et al. (2010) estimated the volume and weight of debris per house and unit floor area. They identified that 30 ~ 113 tons/household of debris were generated based on building types and the level of damaged by a disaster.

Chen et al. (2007) studied the correlation between the volume of debris and flood using the case study of the flood in Taiwan. Three parameters were applied to estimate the volume of debris in a flood scenario: *population density* (x_1), *total rainfall* (x_2), and *flooded area* (x_3). They identified that the high non-linear correlation with the three variables, but, which could be used to predict the volume of debris (y).

$$\log y = -4.137 + 0.718 \log x_1 + 0.600 \log x_2 + 1.422 \log x_3$$

While many scholars developed debris estimation models, there are still high uncertainties and complexities involved in debris generation. In the following sections, this study discusses multiple debris estimation methods.

2.1.2.3 Three methods to estimate debris quantity

FEMA (2010) provided several methods available to estimate the volume of debris. The debris task force leader in FEMA recommended that appropriate method should be selected based on the accuracy level, operation schedule requirements, and resource availability such as personnel and equipment. Three methods are outlined here, and these methods could be combined if needed: Ground measurement, aerial/satellite images, and computational modeling.

2.1.2.3.1 Ground measurement

Ground measurement methods use visual observations and field data collections with measuring tapes and GPS units. FEMA developed an equation to estimate debris quantity associated with demolished single-family residence based on their empirical data studies coming from data collection after Hurricane Floyd in 1999:

$$Debris\ quantity\ = 0.20\ \times Length\ \times Width\ \times S\ \times\ VCM$$

S = *Number of stories in the building*

0.20 = Constant based on the study data

VCM = *Vegetative cover multiplier*

Note: Unit for length and width should be "feet"

For a multiple-story residence, the debris quantity should be calculated using the total number of stories. A list of vegetative cover multiplier is decribed in Table 2-5.

Table 2-5 Table for single-family and single-story home

Typical house (S.F.)	**Vegetative Cover Multiplier (VCM)**			
	None	Light (1.1)	Medium (1.3)	Heavy (1.5)
1000 SF	200 CY	220 CY	260 CY	300 CY
1200 SF	240 CY	264 CY	312 CY	360 CY
1400 SF	280 CY	308 CY	364 CY	420 CY
1600 SF	320 CY	352 CY	416 CY	480 CY
1800 SF	360 CY	396 CY	468 CY	540 CY
2000 SF	400 CY	440 CY	520 CY	600 CY

2.1.2.3.2 Aerial and satellite images

Aerial and satellite images taken before and after a catastrophic event have been used to estimate 1) disaster impact areas and 2) debris quantities and types. Lanorte et al. (2017) estimated agricultural plastic wastes using Landsat 8 satellite images (Landsat 8 satellite orbits the Earth ,and circles the Earth every 99 minutes (USGS 2017)). They applied support vector machines (SVMs) to classify satellite images and estimate the quantities of plastic wastes: SVM is a linear model designed for classification or regression problems. The accuracy and coefficient of the estimation were 94.54% and 0.934, respectively.

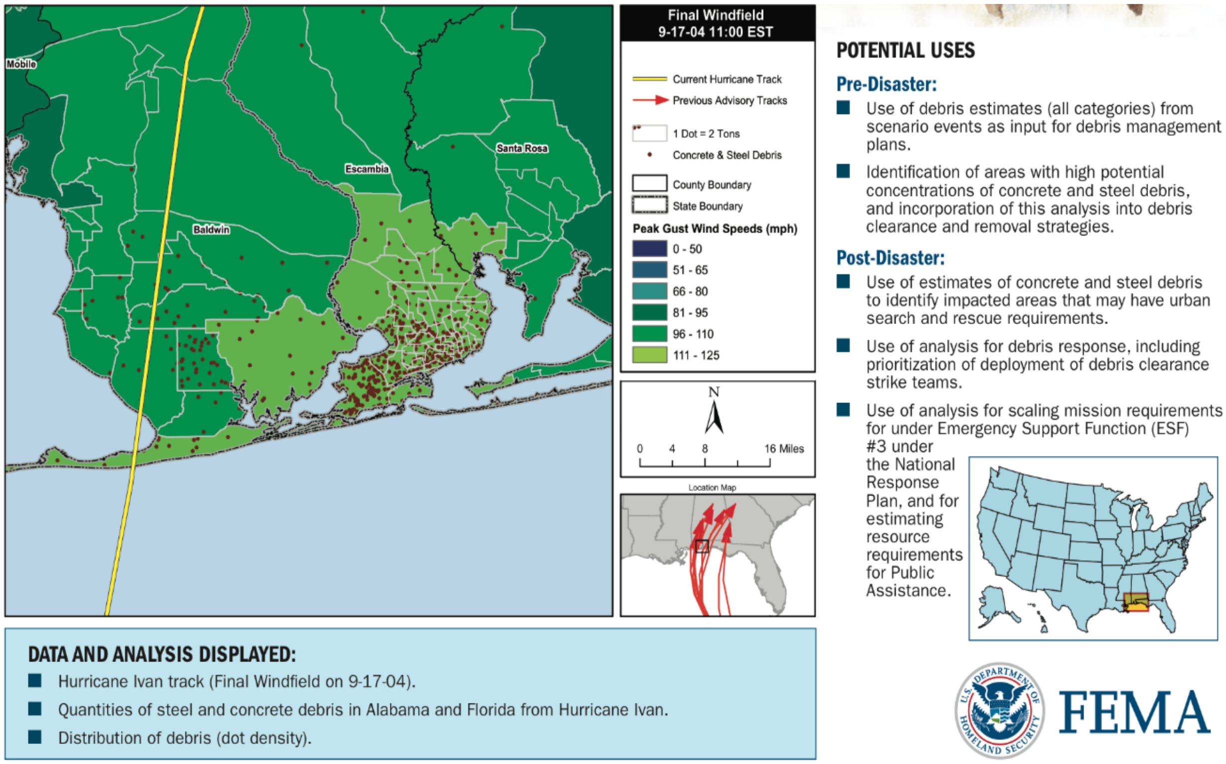
However, using satellite and aerial images has several limitations, including limited accessibility to the public, data acquisition frequency, and weather condition (e.g., cloud can block a certain part of satellite images). To overcome the constraints, unmanned aerial vehicles (UAVs) are frequently used to collect aerial images. Adams et al. (2016) applied UAVs to map the consequence of debris flow in Austria (the accuracy and precision was 0.05 – 0.5m and of 0.05m RMSE, respectively). They highlighted the several advantages of UAV application including higher flexibility, easier repeatability, less operational constraints comparing to satellite data, and high spatial resolutions.

While these image-based methods have very high accuracy and operational flexibility in identifying debris around a disaster-affected community, it is limited to identify the amount of debris inside buildings and houses (e.g., debris inside buildings and facilities is taken out when residents come back after evacuation. It might take a week or more depending on the severity of disasters). It might be tough to estimate debris generation after a flood because of water-damaged properties are mainly in buildings and houses.

2.1.2.3.3 Computational model

In the U.S., Hazus-MH is a standard method to estimate potential losses from multiple types of disasters including earthquakes, floods, and hurricanes (FEMA 2018). It is designed to be integrated into Geographic Information Systems (GIS), particularly ArcGIS, to estimate the physical, economic, and social impacts. In a GIS platform, users can project the spatial relationships between populations and other geographic assets/resources. Hazus-MH's results can be used in an assessment step or the mitigation planning process, which is the foundation for a community's long-term strategy to decrease disaster losses (see Figure 2-1). There are several advantages and benefits on computational modeling and simulation such as Hazus-MH. Remo et al. (2016) applied Hazus-MH's flood loss assessment to support their flood vulnerability index in Illinois. However, they pointed out that national-level infrastructure data in Hazus-MH contains approximations of structure, contents, and inventory replacement values for a specific census block; it could increase the uncertainty of simulation results. They suggested that the results of Hazus-MH might be beneficial for comparative purposes. Shultz (2017) analyzed the accuracy of Hazus-MH general building stock data. They illustrated the two issues in the study: (1) underestimate building square footage (15-20%) and (2) overestimate replacement costs (31-56%). The overestimate could reach between 51 and 81%. As discussed, while Hazus-MH has several limitations on predicting multiple losses by a catastrophic event, it is the only available multi-level disaster-impact assessment tool.

(a) Debris estimation – estimates of debris generated by the Hurricane Ivan



(b) Estimates of debris generated for return period 250-year earthquake

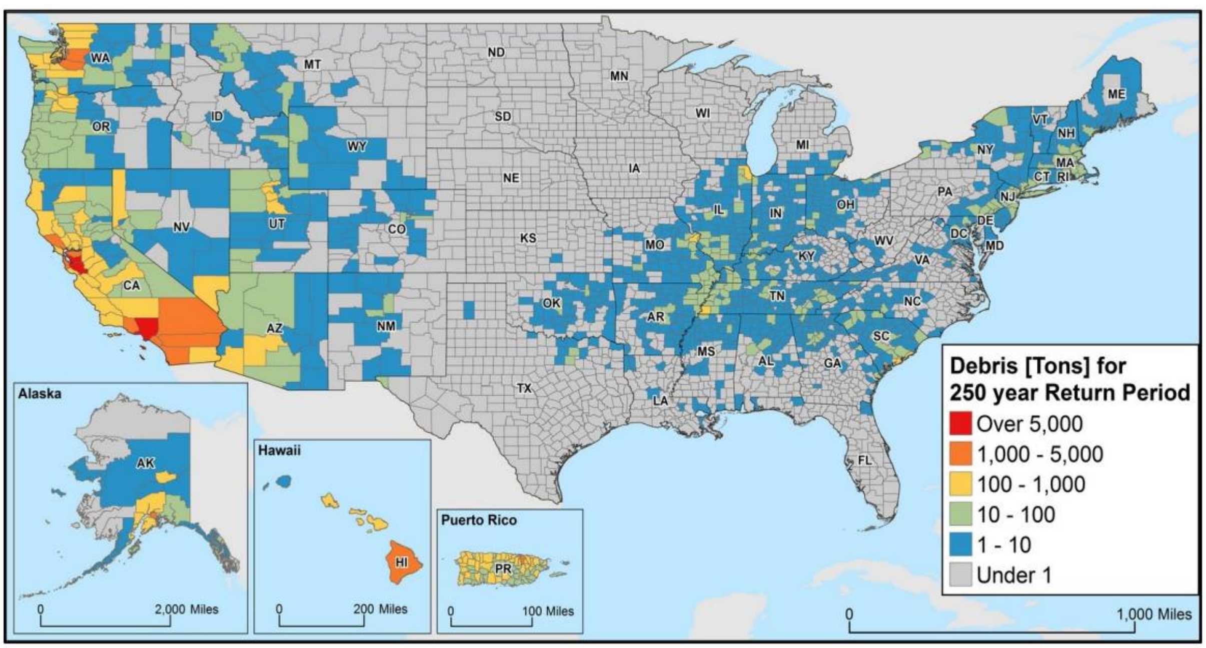


Figure 2-1 Estimates of debris using Hazus-MH

Reference : (FEMA 2013c; FEMA et al. 2017)

2.1.2.3.4 Debris conversion factors

The weight and volume of debris are generally represented using *tons* and *CY*. Thus, unit conversion factors (between weight and volume) are sometimes necessary. USACE developed several conversion factors for converting between weight and volume of debris (see Table 2-6).

Table 2-6 Debris conversion factors

Type	**Ton**	**Cubic Yard**
Construction and demolition debris	1 ton	2 CY
Mixed debris	1 ton	4CY
Vegetative debris (hardwoods)	1 ton	4CY
Vegetative debris (softwoods)	1 ton	6CY

Note: In debris removal practices and reports in the U.S., the unit, CY, is mainly used.

2.1.3 Debris collection and treatment options

2.1.3.1 On-site debris/waste segregation and collection

U.S EPA and FEMA recommend disaster-affected residents to place debris on the curbside (Figure 2-2): Debris should be placed outside of the sidewalk because debris removal contractors are limited to access private property (e.g., inside of the sidewalk). Also, debris on the curbside should be segregated into six categories; *house garbage*, *construction debris*, *vegetation debris*, *household hazardous waste*, *white goods*, and *electronics*. These efforts can increase debris collection performance as well as the recycling rate of mixed debris.

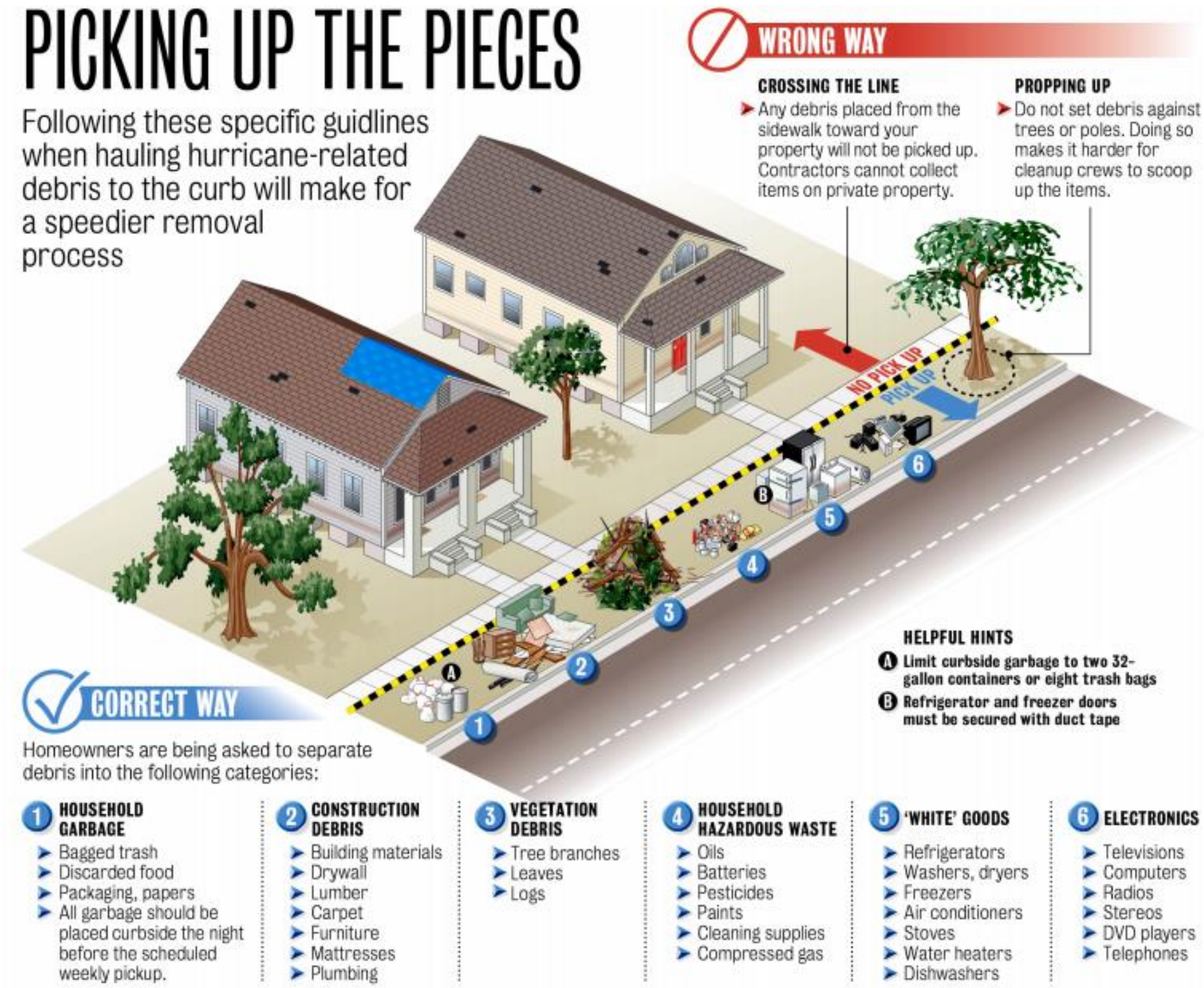


Figure 2-2 U.S. EPA's guideline for debris separation by homeowners

Image from (U.S. EPA 2017a)

Equipment for solid waste collection equipment is limited to be used during the initial stages of debris clean-up because of the size and weight of debris on curbside (Solid Waste Association of North America 2005). In general, a single debris removal contractor is assigned to collect debris on the curbside. They utilize end-dump trucks and tracked excavators with grapples and/or wheeled bucket loaders to haul large-size debris (see Figure 2-3). After a couple of truck passes, traditional collection equipment (e.g., roll-off containers, and rear- and front-end loading packer trucks) starts solid waste collection service.

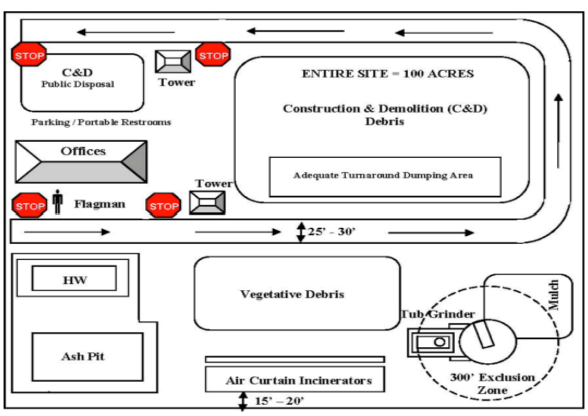
(a) Self-loader truck

(b) Loader + Truck

Figure 2-3 Types of debris collection equipment

2.1.3.2 Temporary debris management site

A temporary debris management site (TDMS) is recognized as one of the critical facilities for effective debris management (FEMA 2007, EPA 2008, UNEP and OCHA 2011). It is mainly designed as a buffer to appropriately sort, recycle, and dispose of debris (FEMA 2007; Lipton and Semple 2012)(see Figure 2-4). To handle 1 million CY of debris, a recommended size of TDMS is 100 acres.



TDMS layout

TDMS during the NYC debris management after the 2012 Hurricane Sandy

Photo by Doug Kuntz, The New York Times

Figure 2-4 Temporary debris management site

There is a trade-off between 1) speed of clean-up, 2) degree of diversion, 3) recycling debris, 4) treatment options, and 5) disposal options (Brown and Milke 2009). The overall period of debris removal depends on 1) selected debris treatment options and 2) resource availability, 3) supporting infrastructure capacity and serviceability. FEMA (2007) released a new pilot program providing incentives for debris recycling efforts. Fetter et al. (2010) developed a decision model with recycling incentives for locating TDMSs.

Breezy Point, NY after 2012 Hurricane Sandy

Photo by Tim Burkitt/FEMA

East Baton Rouge, LA after the 2016 Louisiana flood

Photo by J.T. Blatty/FEMA

Figure 2-5 Operations in TDMS

Note: The images were reprinted from FEMA (2014a; b, 2016b)

However, an inappropriate location of TDMSs can bring unexpected or negative effects. For instance, TDMS operation can bring extra expenses for double-handling debris and acquiring lands (FEMA 2007). Also, locating TDMSs in unsuitable areas such as playgrounds, swamps, and rice paddies can potentially affect the environments and the livelihood of residents nearby (Kim et al. 2018a).

A TDMS may 1) attract rodents and other pests, 2) make noise, 3)produce odors that can be easily above the acceptable level of residents nearby, and 4) increase traffic nearby. Thus, US EPA (2008) provided several guidelines:

- *Sufficient size of TDMS*
- *Appropriate topography and soil type.*
- *Certain distance from rivers, lakes, and water streams.*
- *Distance from floodplains and wetlands.*

- *Avoid any obstructions, including power lines and pipelines.*
- *Close to a disaster-affected area, but far enough away from residential and commercial areas and infrastructure facilities that could be easily affected during TDMS operations.*
- *Locate in public land because the approval process is easier. However private lands can be used if necessary: consider potential agreements on the land uses with private landowners in advance.*

While identification of TDMS in a pre-disaster scenario has been studied as a way to avoid potential adverse effects (Kobayashi 1995, Skinner 1995, FEMA 2007, USEPA 2008, Johnston et al. 2009), most of the existing guidelines focus on environmental regulations. Further research is required to explore technical and social impacts of TDMS location in a short- and long-term period.

Recently, emergency agencies take an effort to share TDMS operation information during debris removal. For example, the Texas Commission of Environmental Quality opened multiple TDMSs to handle debris generated by the 2017 Hurricane Harvey. The TDMS information was shared by their GIS platform (Texas Commission on Environmental Quality 2017). It included site contact information and accepted type of debris in each facility (see Figure 2-6).

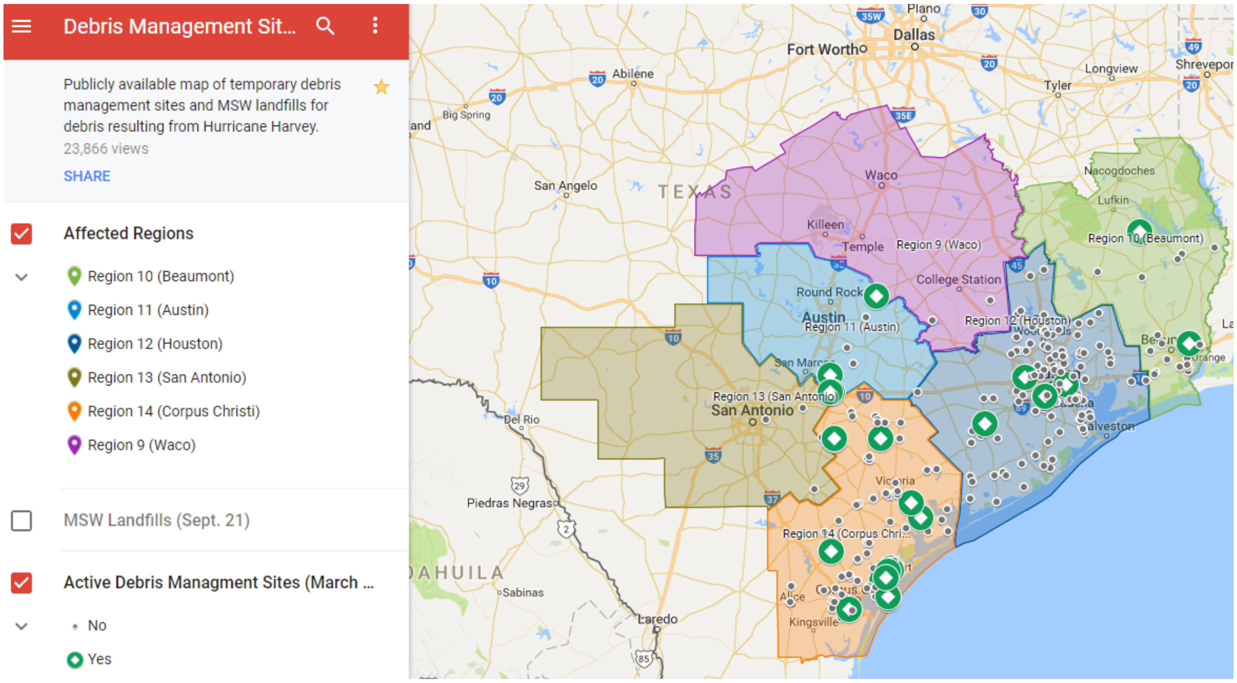


Figure 2-6 TDMS locations during debris removal after Hurricane Harvey in Texas, USA

2.1.3.3 Recycling

U.S. EPA (2009) recommended that a debris management plan should include specific resue, recycle, compost strategies for multiple types of debris. These efforts can reduce 1) capacity burdens in TDMS and landfills, 2) decrease potential costs, and 3) provide a valuable material resource from recycled debris. It is also reported that most of debris components are recyclable. These materials can be reused for several post-disaster applications, including soil for covering landfills; aggregate for concrete; and plant material (Channell et al. 2009). The benefits from debris reuse/recycling have been discussed in multiple debris management practices: Marmara earthquake (Baycan and Petersen 2002, Baycan 2004); Northridge Earthquake (Gulledge 1995, USEPA 2008); Indian Ocean Tsunami, Thailand, and Sri Lanka (UNDP 2006). The benefits of recycling debris are the followings:

- *Reduction of landfill capacity required*
- *Revenue generation*
- *Cost reduction from transporting raw materials and debris*

- *Job creation (for developing countries in particular)*

The main component of disaster debris is construction and demolition (C&D) waste. While Reinhart and McCreanor (1999a) and Skinner (1995) provided recommendations for recycling C&D debris and practices, other studies identified existing barriers on C&D recycling (see Table 2-7).

Table 2-7 Main issues on C&D recycling during debris removal

Issues	**References**
Time consuming to collect/sort/process recyclable debris	Baycan and Petersen 2002
Require special equipment and facilities	Baycan and Petersen 2002 Baycan 2004
Lack of market for recycled materials	Lauritzen 1998
Facility capacity to handle the large amount of recyclable debris	

Whereas the literature above provides the advantages and existing obstacles to debris recycling, there have been no quantitative assessments or feasibility analysis for post-disaster recycling options. For instance, the recycling capacity in California is estimated to be approximately 60 million tons per year (Yesiller 2012): The available recycling capacity is considerably less than the available disposal capacity.

2.1.3.4 Open burning and air curtain incineration

Two burning methods are recommended: *open pit* and *incinerator*. These burning methods had been used in multiple debris removal operations such as the Indian Ocean Tsunami (Basnayake et al. 2006), and the Great Hanshin-Awaji earthquake (Irie 1995). Lauritzen (1998) and Petersen (2004) highlighted that open burning is appropriate in certain situations, but a few guidance exists U.S. EPA (2008) reported that a portable air curtain incinerator is am efficient debris burning method. During disaster recovery after Hurricane Irma and Maria, multiple air curtain incinerators were operated under the supervisions from USACE and US EPA: This method was applied as 60% of debris generated (850,000 CY) were identified as trees, fronds, brush, and grass. (FEMA 2017a).

Figure 2-7 Air curtain incinerator (left) and open burning system (right)

Photo credit: Clay Church and Billy Birdwell / USACE

2.1.3.5 Debris disposal

Direct disposal of debris generated is the fastest way to clean up debris on a community, but there are significant concerns on debris disposal options. FEMA recommends that municipal officials should determine debris collection and disposal options suited for their own circumstance/situation. However, in the aftermath of large-scale disasters, the volume of debris significantly exceeds the existing capacity and serviceability of permanent disposal sites (EPA 2008). Also, mixed debris on sites hampered the general debris separation/transportation process. While a TDMS plays a critical role as a buffer to reduce the volume of debris transferred to landfills as well as sort out mixed debris, mixed debris with hazardous materials can be transported to landfills without any appropriate sorting or treatment process.

For asbestos and other hazardous materials, there are several regulations and policies from FEMA, U.S. EPA and the state's department of environmental protection. However, several studies identified that these hazardous materials were transported to landfills without appropriate sorting or treatments (Brown et al. 2011; Channell et al. 2009; Dubey et al. 2007). There are still few studies investigating environmental effects from hazardous substances in disaster waste and landfills.

2.1.4 Disaster debris management facility database

There are ten US EPA regional offices and each office is responsible for several states (U.S. EPA 2017b).

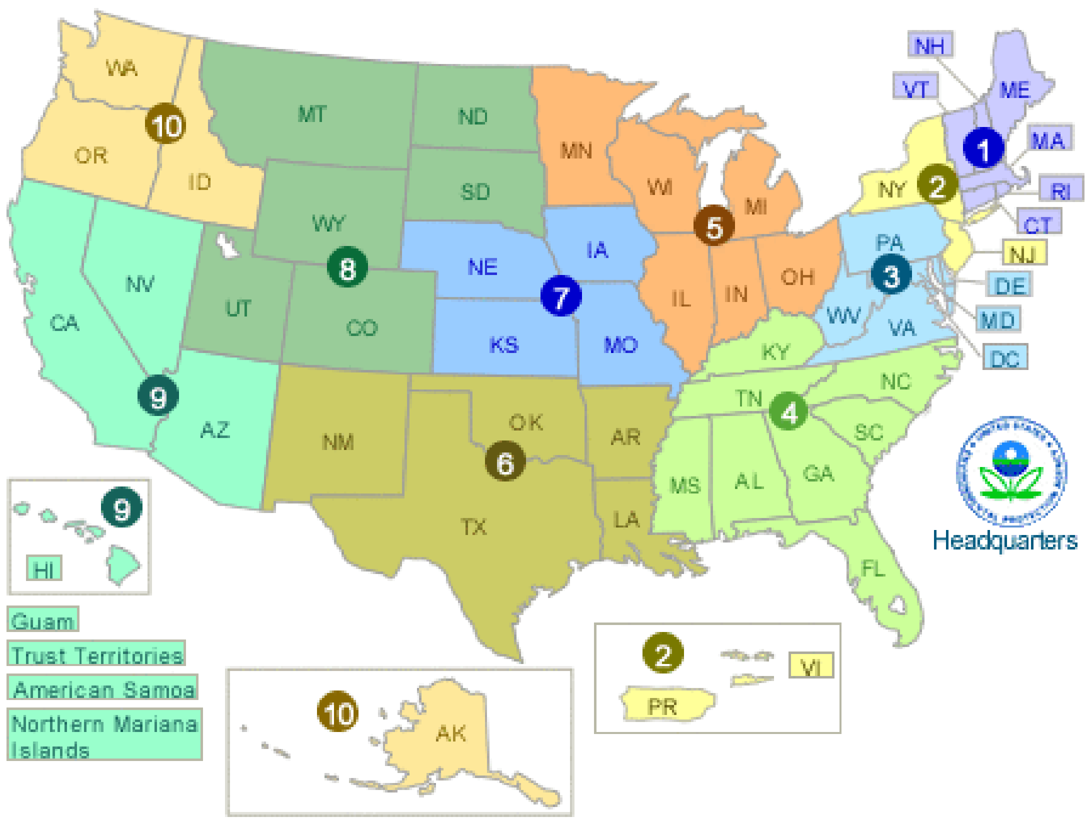
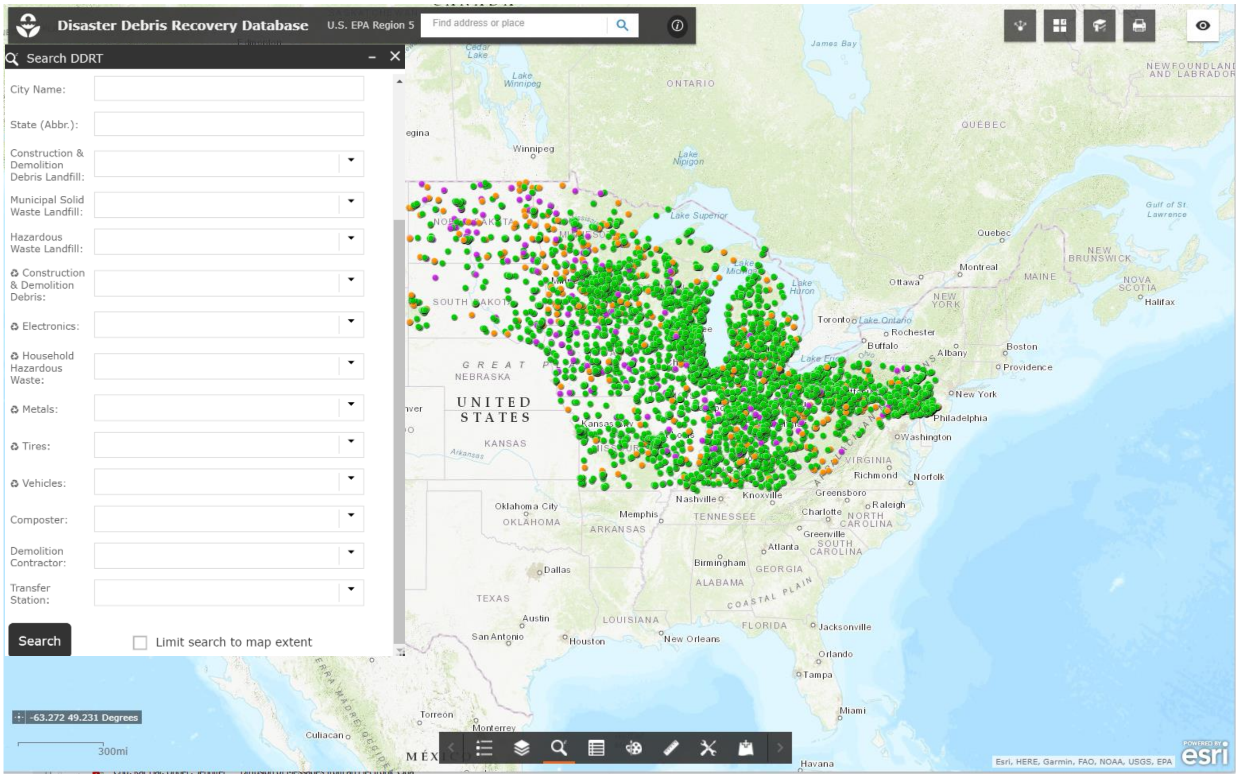


Figure 2-8 US EPA regions

(Image from U.S. EPA)

Recently, EPA Region 5 developed a database of 12 types of landfills and recyclers managing disaster debris in the region. The GIS-based interactive map provides information and location of over 6,000 facilities capable of managing different types of (US EPA 2017b).



data link: https://r5.ercloud.org/WAB/DDRT/

Figure 2-9 Information and locations of disaster debris related facilities in EPA region 5

Note: Green, orange and purple points on the map represent recyclers, landfills and landfill & recyclers, respectively. In the search bar on the left side, a user can identify facilities handling a specific type of disaster debris.

2.1.5 Issues on disaster debris management

This study classified multiple issues reported during debris management into three categories (economic, environmental, and social issues) and discussed it with case studies.

2.1.5.1 Economic impacts

A disaster creates a huge financial burden on the state- and local municipals to clean up a tremendous amount of debris generated. Costs for debris removal consist of direct and indirect costs. Direct costs refer to costs used for debris cleanup, and indirect costs refer to any costs made from debris treatment/removal options.

Direct costs include debris collection, treatment and disposal costs. FEMA (2007) analyzed debris removal costs during disaster recovery between 2007 and 2007. They reported that 27% of the total disaster recovery costs spent for debris removal. Similarly, Califonia Emergency Management Agency (2011) informed that direct debris removal costs could be up to 40% of the total disaster recovery cost.

Indirect costs are defined as all costs associated with any follow-up activities from delayed debris removal or losses from different debris treatment options. Thus, it is relatively difficult to estimate/report than direct costs. For example, delay in debris removal may result in 1) public health issues (e.g., noises and odors from TDMSs, and heavy traffic nearby), 2) environmental contaminations and 3) illegal dumping of hazardous or mixed debris. Also, inappropriate debris treatment options may delay in debris removal speed as well as result in ground contaminations from mixed or hazardous debris. Cost-benefit analysis for multiple debris treatment and removal options has been done (Bolyard and Reinhart 2016; Petersen 2004; Reinhart and McCreanor 1999a; UN 2011) such as (1) cost minimization under the parameters including disposal, transportation and equipment type, (2) revenue generation through recycling, and (3) job creation. While recycling materials during debris management are highly recommended, cost-benefit analysis should be conducted to compare benefits and losses generated from recycling options. Methods including life cycle assessment (LCA) or life cycle cost (LCC) are recommended to be employed in recycling options. Wakabayashi et al. (2017) applied LCA and LCC frameworks to evaluate environmental and economic costs for multiple debris removal strategies.

So far, a few information or reports regarding debris removal costs are accessible. In the U.S., FEMA shared historical debris removal funds (i.e. public assistant grant program). This study summarized the published debris removal cost data in Table 2-8.

Table 2-8. Historical debris removal cost

Event	Location	Debris quantity*	Cost ($)	Reference
Hurricane Katrina	LA, USA	118 million cubic yards	4.1 billion	Luther (2010)
Indian Ocean Tsunami(2004)	Sri Lanka	0.5 million tons	5-6 million	Basnayake et al. (2006)
Indian Ocean Tsunami(2004)	Thailand	0.8 million tons	2.8 million	Basnayake et al. (2006)
Typhoon Tokage(2004)	Tokage, Japan	44,780 tons	15-20 million	UNEP (2005)
Hurricane Charley	FL, USA	19 million CY	286 million	FEMA (2009)
Central Florida Tornado	Osceola County, US	250,000 CY	8 million	Reinhart and McCreanor (1999a)

Note: Unit for debris quantity is either CY or tons. This study used the original unit used in the references.

Reinhart and McCreanor (1999) and the Solid Waste Authority (2004) pointed out the reported debris removal costs were sometimes inconstant, or it only included small parts such as unit cost for cubic yard, disposal costs, or costs in small part of disaster- affected areas. Most of them did not include costs from individual clean-up efforts. Thus, it is required to investigate the entire debris removal mechanisms to understand the fundamental characteristics of debris removal costs.

2.1.5.2 Public health and environmental impacts

In a phase of post-disaster debris management, the debris removal speed is critical. Consequently, the majority of debris-related studies and reports have focused on maximizing debris removal performance. Few studies attempted to measure the environmental impacts (Brown et al. 2011). For example, Dubey et al. (2007) investigated the quantity of arsenic disposed in demolition debris (e.g., treated wood) after the Hurricane Katrina,. They emphasized the potential for leaching of arsenic from pressure-treated wood should be examined and studied. Chandrappa and Das (2012) discussed possible public health problems from (1) human contact (2) vectors and rodents, (3) collapse of disaster-damaged structures, and (4) environmental system disturbance (e.g., change in the population of certain species, and loss of agricultural crops areas).

2.1.5.3 Human/social behaviors in a disaster

Before collecting debris on the curbside, residents need to segregate on-site debris based on guidelines from local emergency agencies. However, Returning to their houses or properties might take several days or weeks depending on disaster impacts and their property damages (Groen and Polivka 2010). For example, most of residents in Louisiana were not able to return to their houses because of severe disaster impacts and damaged their properties (Luther 2008): the population in Orleans and St. Bernard parishes reached around 70% and 41% of pre-Katrina levels for more than two years. This slow return of residents resulted in the higher number of debris removal truck passes on each road segment. According to the USCE, debris collectors generally pass two or three times to collect debris. More than 20 truck passes, however, were made in the certain areas in Louisiana (Luther 2008). Thus, this relationship between resident return rates should be integrated into debris management systems to enhance the overall debris removal performance (truck routing and allocation) as well as identify the optimal number of equipment (trucks) over time. Brown et al. (2011) proposed further research on psycho-social implications in the speed of debris removal process, and emotional attachment on certain items in mixed debris.

2.1.6 Factors on debris management performance

To maximize debris removal performance, a debris management team should recognize existing waste management systems and debris management plans. In general, debris management systems are operated based on existing solid waste management systems. For example, temporary debris management sites and additional resources such as mobile incinerators, hauling trucks, and power generators are integrated into the existing solid waste management systems (see Figure 2-10).

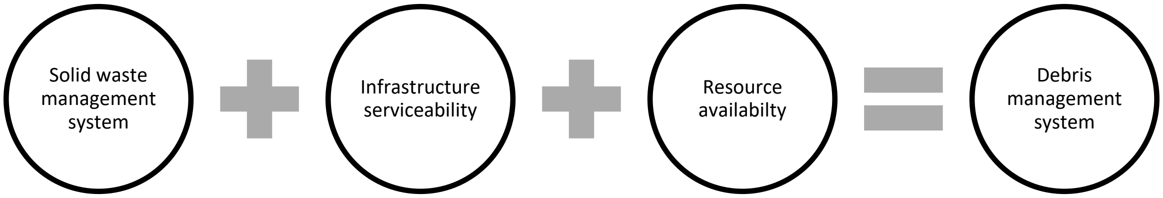


Figure 2-10 Process to build an effective debris management system

Guerrero et al. (2013) examined various factors related to waste management performance (see Table 2-9). They identified critical infrastructure including transportation, technologies, and facilities for treatment, recycle and disposal. Critical resources are identified as hauling trucks and other equipment including incinerators, chippers and grinders (Karunasena et al. 2009). Finally, they highlighted that knowledge in debris treatment and disposal options are beneficial to maximize debris removal systems (Guerrero et al. 2013).

Table 2-9 Waste management factor analysis

Stage	Affecting factors
Collection, transfer and transport	Truck routing and allocation
	Infrastructure capacity and serviceability
	Type of resources for collection
	Waste management organization structure
	Transportation
Treatment	Knowledge and information for treatment options
	Knowledge of existing waste management issues
Disposal	Containers and hauling distances
	Disposal price ($/cy or $/ton)
Recycle	Recycling markets
	Capacity of Recycling facility
	State- and local government's financial support
	Collection efficiency (sorting process)
	Technologies for low-cost recycling process

Reference: (Guerrero et al. 2012)

2.2 Critical infrastructure related to disaster debris removal

Critical infrastructure's capacity and serviceability significantly affect the performance of post-disaster debris management systems. Thus, infrastructure capacity and serviceability are considered as one of critical components in disaster debris management systems. *ASCE (2006)* defines critical infrastructure as "*any systems and assets that is so critical that any destructions on systems would have tremendous impacts on national economy, public health and safety. It includes built environments, natural and virtual systems".*

Bruneau et al. (2003) examined infrastructure resiliency by four determinants: *robustness, redundancy, resourcefulness,* and *rapidity*. In addition, Deshmukh and Hastak (2009) mentioned that the impact of disasters is further escalated by failures of any component of critical infrastructure systems. To prevent cascading failures, capacity building of critical infrastructure is essential for community resiliency (Deshmukh and Hastak 2012): They defined *capacity* as available resources after a disaster and *capacity building* as the ability to acquire additional capacity on existing infrastructure capacity. While several types of critical infrastructure are defined, this study focuses on three types of infrastructure: civil, civic, and social infrastructure.

2.2.1 Civil infrastructure

Civil infrastructure such as transportation, power systems and waste management systems is considered as a critical component in disaster debris management systems. The capacity and serviceability of infrastructure systems during or after a disaster directly affect the entire debris removal performance. According to the ASCE, the average GPA of US infrastructure was D+ in 2017: Most of the critical infrastructure related to debris management received low grades such as bridges, dams, energy, hazardous waste, levees, ports, rail and solid waste (see Figure 2-11).

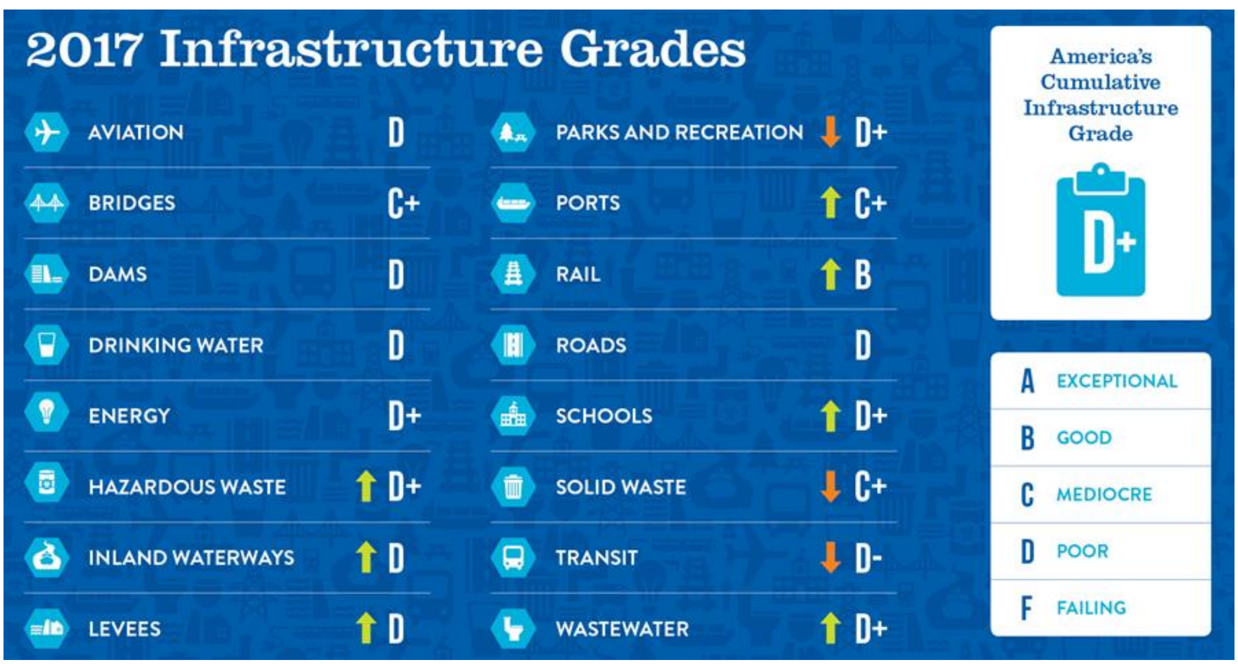


Figure 2-11 2017 U.S. Infrastructure grades

American Planning Association (2014) emphasized that continuous resilient planning by communities advanced a more resilient infrastructure system from a catastrophic event. They highlighted four points below:

- Understand the risks to infrastructure.
- Identify risk mitigation actions and the implementation feasibilities in terms of functional benefits, costs, and impacts
- Identify federal, state and local-level funds for mitigation planning as well as a partnership with utility companies of critical infrastructure

Here is an example of how Infrastructure failures in terms of capacity and serviceability affect debris removal. The Haitian government highlighted debris removal (13 million CY of debris) is one of their top priorities after the 2010 Haiti earthquake. However, the tremendous amount of debris in the city hampered emergency response and recovery projects (UN Development Programme 2010). Damaged infrastructure and insufficient resources also delayed in transporting debris to designated locations. After several months, cholera outbreaks began in October 2010 and killed at least 7,000 Haitians (It was recorded as the worst epidemic (WHO 2017)). Even after an year of the earthquake, only 3~10% of the total debris was removed (UN 2011).

2.2.2 Civic infrastructure

Civic infrastructure entails debris-related regulations and policies from governmental agencies. In the U.S., state- and local-agencies have responsibilities to manage their own debris generated. Federal agencies, including FEMA, USACE, and U.S. EPA often provide grants for debris removal or are directly involved in certain activities such as monitoring debris treatment options or providing equipment (Luther 2017). During the 2019 Nebraska flood, USACE supported right-of-way clearance, debris pickup on curbside and private property, and demolition (FEMA 2019a). U.S. EPA awarded $100 million to the city of Flint, Michigan, for replacing or upgrading water infrastructure, including pipelines (US EPA 2017c).

The DHS (2011) highlighted that municipal officials should monitor debris collection activities on site because most of the debris removal costs are coming from over-estimated volumes of collected debris. For example, FEMA identified that they might have overpaid $20 million for debris removal and disposal because 1) qualified monitors did not exist, and 2) the overestimated debris load volumes occurred after Hurricanes Gustav and Ike (FEMA revealed that an overestimated volume would be 20% or more). Currently, guidelines for debris pickup monitoring are limited to use existing guidelines from FEMA or U.S. EPA. For a better debris monitoring system, local-level municipals should include step-by-step debris monitoring guidelines based on their unique debris management circumstances as well as monitoring techniques/methods. While it is not realistic to manually monitor all of hauling trucks coming to a TDMS, laser scanning methods and equipment (e.g., LoadScanner) could be an alternative to measure the volume of debris in a hauling truck. Finally, most of the debris removal contacting is unit-price contract (that is very common contract type in particular public works such as road construction and maintenance).

Further research is required to examine the benefits of laser scanning systems as well as different contract types for debris removal. These regulations and policies should be examined and developed by collaborations with federal, state- and local emergency agencies.

2.2.3 Social Infrastructure

Studies on critical infrastructure have been focusing on securing and protecting hard capital resources such as facilities and technologies for a while. While studies and recognition of soft capital (e.g., people and knowledge) has been slower than other infrastructure, many scholars start investigating social infrastructure as a critical component for community resiliency (O'Sullivan et al. 2013). Nakagawa and Shaw (2004) identified that both leadership and social capital are critical attributes for rapid disaster recovery. They also investigated the relationships between three aspects of social capital: *bonding*, *bridging* and *linking (see* Figure 2-12). Aldrich (2011) highlighted that the power of people is the most robust predictor of disaster recovery performance. Aldrich and Meyer (2014) highlighted that emergency agencies and local municipals should strengthen social infrastructure at the community level.

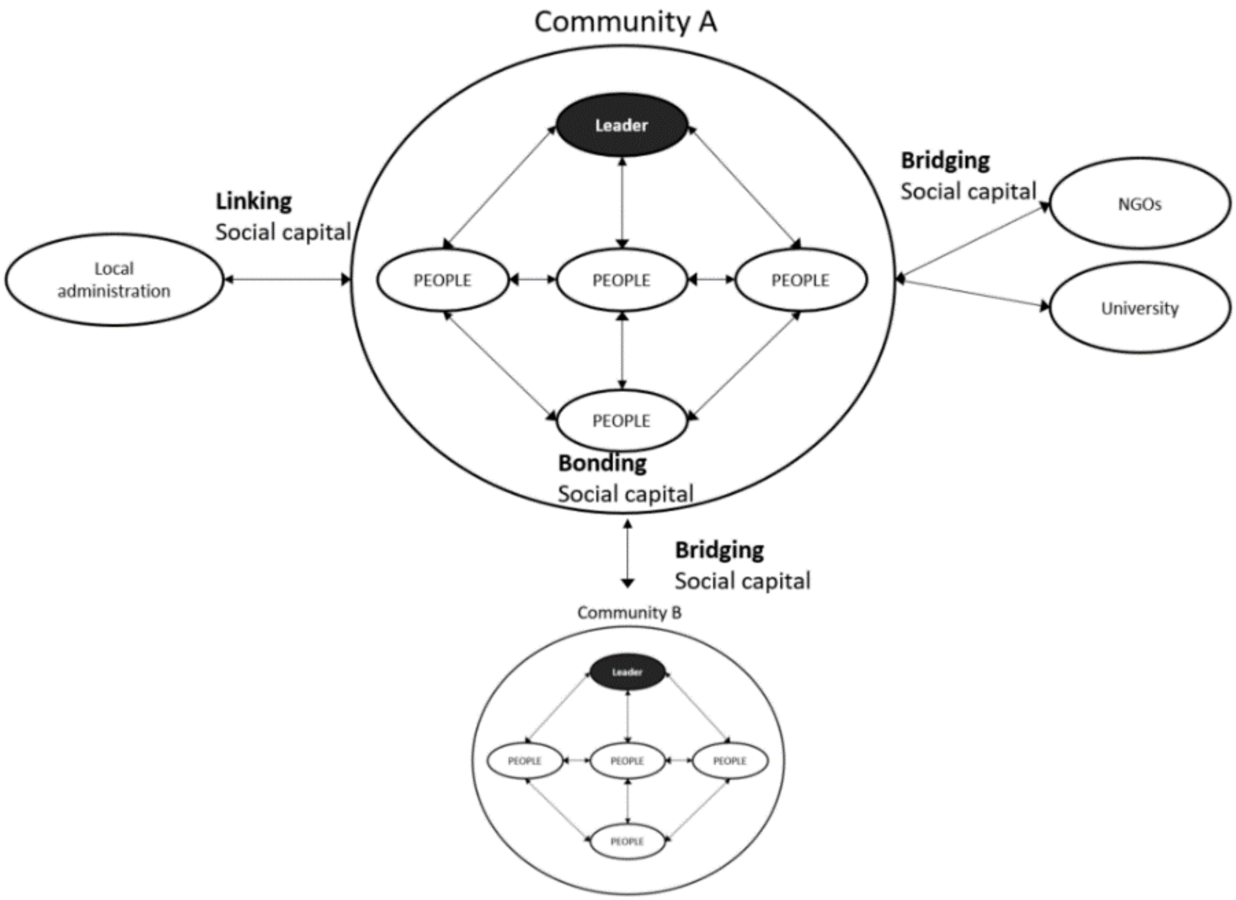


Figure 2-12. Conceptual diagram of social capital

Note: the image is re-created based on the original image by (Nakagawa and Shaw 2004)
Many scholars also investigated social media, as one of social infrastructure as a communication channel, during a disaster. Liu et al. (2014) studied emergency information channels and sources in terms of their ability to generate desired public outcomes. Kim and Hastak (2018) demonstrated how disaster-affected communities and external organizations were linked through social media, and bonded together to improve information diffusion during the 2016 Louisiana flood. It is well-recognized that governments alone cannot achieve significant, sustainable emergency information systems.

2.3 Complex system and system modeling

Systems are defined as a sum of entities with well-defined components. In general, simple systems are characterized by few components with their static or dynamic behaviors. It can be understandable and predictable. For example, hauling truck systems (considered as a part of debris management systems) can be represented by trucks (entities) and truck behaviors (components). If hauling truck systems consist of a single hauling truck and one route (with a single point of origin and destination), the systems can be considered as simple systems: It can be easily understandable and predictable. Several methods are applicable to develop a prediction model such as mathematical modeling and simulation (Fortunato 2010; Grabowski and Strzalka 2008a).

Comparing to simple systems, complex systems have many components that collaborate to create a functioning whole. Here are several definitions of a complex system.

"A system comprised of a (usually large) number of (usually strongly) interacting entities, processes, or agents, the understanding of which requires the development, or the use of, new scientific tools, nonlinear models, out of equilibrium descriptions and computer simulations." [Advances in Complex Systems Journal]

"A system that can be analyzed into many components having relatively many relations among them, so that the behavior of each component depends on the behavior of others. "[Herbert Simon]

"A system that involves numerous interacting agents whose aggregate behaviors are to be understood. Such aggregate activity is nonlinear; hence, it cannot simply be derived from the summation of individual components behavior." [Jerome Singer]

The comparison between simple and complex systems is described in Table 2-10.

Table 2-10 Basic properties of simple and complex systems

	Simple systems	**Complex systems**
Exploitation / Physical parameters	Specialized structures (dedicated) deterministic, circuit switching Algorithmic processing	Structures for general use, non-deterministic, packet switching interactive processing
	Executing structure and connections topology fitted to tasks unchanged in time Linear scalability, unbounded system resources	Volatility of tasks lead to mismatch between executing structure and connections
		Non-linearity of characteristics (e.g., performance and response time)
	Lack of congestions and collapse Static planning of performance, Mean Value analysis	Sensitivity to congestions and infections, constant collapse
	Process control independent of system re-sources management	Dynamic planning of performance at the edge of chaos
	Static or dynamic workload equalization, but short-range dependent (post-fact) guaranteed quality of service	Process control and resources management connected together
		Dynamic workload equalization with long-term control prediction

Reference: (Grabowski and Strzalka 2008b)

Borshchev and Filippov (2004) mentioned "*Modeling is a way of solving real-world problems when prototyping or experimenting within the real systems is expensive or almost impossible*". Complex systems can be approached by analytical and simulation modeling (see Figure 2-13).

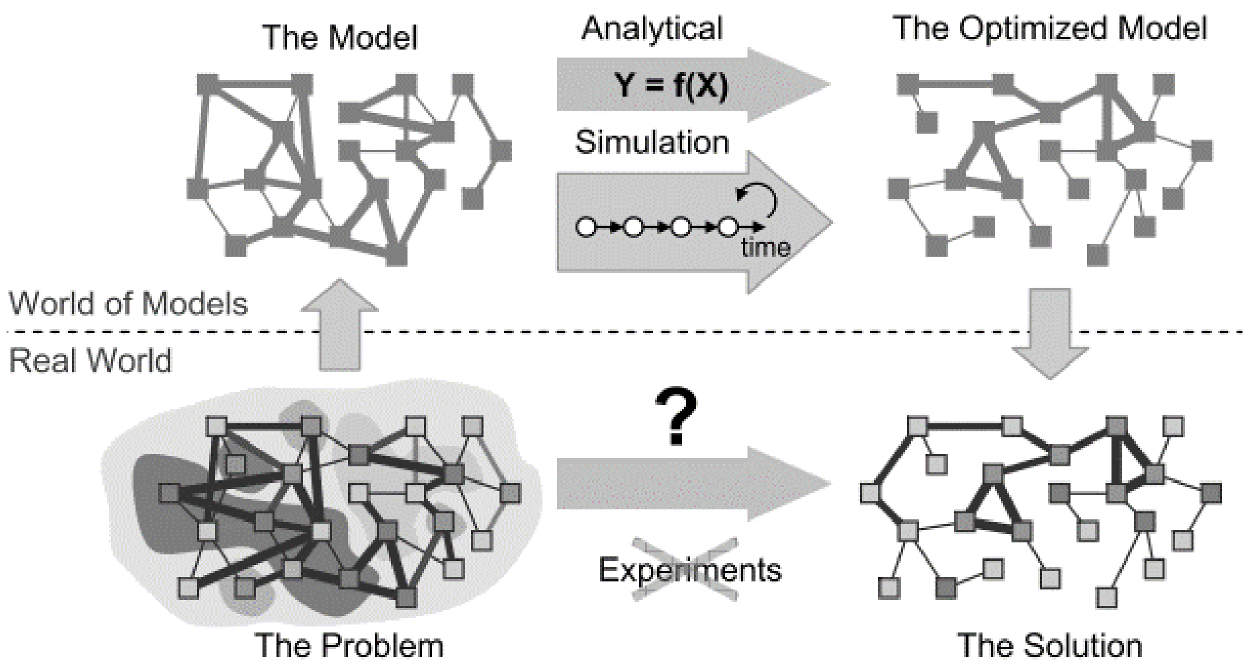


Figure 2-13 Analytical (static) and simulation (dynamic) modeling

image from Borshchev and Filippov (2004)

Analytical (static) model: An analytical model is quantitative and computational. It represents a system with a set of mathematical equations: it specifies parametric relationships and their associated parameter values as a function of system parameters (e.g., time and space) (Friedenthal et al. 2015). This process can be accomplished by modeling the underlying phenomena to predict or assess how well the system performs or other system characteristics.

An analytical model characterizes parameter values that do not change over time. An analytical model may be solved via a closed form solution (e.g., an equation is called as a closed-form solution if it solves a given problem in terms of functions and mathematical operations from a given generally-accepted set). For example, it includes the position of a point mass given an initial position, velocity, and acceleration. Other solutions require numerical analysis methods to determine the change in state of the system as a function of time, space, and other parameters. Finally, parameter values can be deterministic or probabilistic. In the latter case, parameters may be defined with an associated probability distribution.

Simulation (dynamic): In the simulation, a modeler considers a set of rules such as equations, flowcharts, state machines, cellular automata. It defines how the designed system will change in the future (given its present state). That is, simulation is the process of model "execution" that takes the model through (discrete or continuous) state changes over time. In general, simulation modeling is better suitable for understanding complex systems where time dynamics are essential.

In a simulation, three system modeling methods are generally applied to analyze system interdependence and performance under different scenarios; discrete event, system dynamics and agent-based model.

Discrete Event (DE): Connelly and Bair (2004) applied discrete event simulation (DES) to advance system-level investigation of emergency department operations. They developed the Emergency Department SIMulation (EDSIM) to simulate ED activity at a Level 1 trauma center. Duguay and Chetouane (2007) applied DES to reduce patient waiting times and improve overall service delivery and system throughput. They compared multiple scenario results to identify feasible operation planning. Siddiqui et al. (2017) illustrated that high variability in patient flow and changing patient acuity in perianesthesia care units is a challenge to the efficient management of nurse staffing. They applied DES to evaluate nurse staffing levels in perianesthesia care units. They verified the application of DES at estimating staffing levels in multiple scenarios.

System Dynamics (SD): Lane et al. (2000) studied complex hospital systems including the interaction of demand patterns, accident and emergency resource deployment, other hospital processes, and bed numbers using system dynamics.
Peng et al. (2014) proposed a system dynamics model to analyze the dynamic behaviors of the disaster relief supply chain by experimenting the uncertainties associated with predicting the post-seismic road network and delayed information. Langroodi and Amiri (2016) studied multi-level, multi-product and multi-region supply chain systems under demand uncertainty. They simulated the supply system under normal conditions, oscillating demands, variations in price, changes in costs, and a combination of these variations. Kim et al. (2018b) investigated the system interdependency related to disaster debris removal including the amount of debris generation, serviceability of transportation, facility capacity and available resources using SD.

Agent-Based Model (ABM): Agent-base model has been used in disaster-related evacuation models. Wagner and Agrawal (2014) investigated crowd evacuation modeling using agent-based modeling. It allowed for multiple scenario testing and decision support for the planning and preparedness s phase of emergency management with regards to fire disaster at concert venues. Tan et al. (2015) also developed an agent-based simulation model by combining human behavior with predictable spatial accessibility in a fire emergency. Wang et al. (2016) studied a multimodal evacuation simulation for a near-field tsunami through ABM in Netlogo to identify impacts of varying decision time on the mortality rate, different means of transportation and impacts of vertical evacuation gates on the estimation of casualties.

A comparison of three system modeling methods is described in Table 2-11

Table 2-11 Summary of three simulation methods including SD, DE and ABM

	System dynamics (SD)	**Discrete Event (DE)**	**Agent-Based Model (ABM)**
Features	- Applied to understand complex system behaviors for a long-term and emergent behaviors from feedback loop - Understand system flows under certain scenarios - Widely applied in policy research at a strategic level	- Applied systems having a queue network (e.g., pedestrians or bank service line) - Focus queue system in a process - Widely applied for equipment operation	- Applied to identify interactions of agents in the environment - Bottom-up approach
Advantages	- Identify the relevant factors that exist in complex systems - Scenario testing can be modified based in order to get different results	- Flexible to design agent behaviors in a system - Straightforward modeling approach once problem set is clearly defined	- Identify emergent agent behaviors in a designed system
Disadvantages	- Not easy to represent too complex system with many components - When not easy to identify clear problem set from the real-world, it is hard to implement in SD	- Not applicable for human behaviors	- Require higher computational skills to develop a large complex system - Require tremendous efforts to design each agent based on observations or dataset

Reference: (Borshchev and Filippov 2004; Sumari and Ibrahim 2013)

Borshchev and Filippov (2004) suggested that a simulation is an appropriate tool for solving complex problems with emergent dynamics. Fiedrich and Burghardt (2007) emphasized that agent-based modeling can be used to support multiple phases of the disaster management from mitigation to emergency response/recovery. Many studies have focused on generic research on agents and possible applications in the domain of disaster management such as robocup rescue (Kitano and Tadokoro 2001), combined systems (Veelen et al. 2006), Aladdin (Jennings et al. 2006), EQ-Rescue (Fiedrich 2006), or FireGrid/I-Rescue (Tate 2006).

2.4 Point of departure

In this chapter, this study systematically summarized cutting edge knowledge and debris management process, related policies and regulations to handle debris generated. While many studies explore the multifaceted and complex post-disaster management, there are few studies developing a model adapting system-of-systems approaches to capture the complexity and dynamics during disaster debris operation. Also, the research body still lacks a set of theories and organized framework that will be critical for researchers, agencies and practitioners in the area of post-disaster management. Finally, there is a need to increase the transparency of the decision making especially with respect to compromise between engineering/technical efficiency for social/political reality of the context: traditional methods of risk assessment to analyze dynamics of the context and do not facilitate the integration of behavior of different actors within the decision context.

To sum up, an effective disaster debris management system is required to cover the entire disaster debris management operation, including the collection, processing, recycling, and disposal stages. Disaster debris management is still understudied (Mendonça et al. 2014), despite the extent and criticality of its impact on economic, environmental, and social dimensions of recovery plans. Current studies underestimate emergent dynamics of debris management, social and political dynamics associated with prioritizing its collection or disposal locations, as well as real-time management of resources such as equipment fleets. In addition, different agencies lack established channels to communicate debris removal strategies and operation plans as platforms for collaboration to expedite the entire recovery process. The extent and criticality of disaster debris management necessitate an adaptive decision support system, which reflects 1) the unexpected impacts of a disaster, 2) characteristics of the community, its interdependent infrastructure network and its social and political dynamics, and 3) efficient utilization of available resources and infrastructure in real-time.

CHAPTER 3. RESEARCH METHODOLOGY AND FRAMEWORK

3.1 Introduction

To navigate the complexity of post-disaster debris management systems, a new paradigm is required that optimizes the debris management system by analyzing the system behaviors under different planning and operational strategies that effectively adapt both the uncertainty of a catastrophic event and the interdependencies within the components of the debris management system. In this chapter, this study introduces a research framework and methodologies used for developing an adaptive decision support system (DSS) applying an adaptive system of systems approach for effective debris management under the considerations of the uncertainty of a catastrophic event and the interdependency in the sub-systems of the debris management systems.

Figure 3-1 describes the proposed research methodology framework. The research methodology framework consists of four phases: a literature review, a methodological framework for the adaptive decision support system, the development of an adaptive decision support system, and the application of the decision support system within debris management in the city of Baton Rouge after the 2016 Louisiana flood.

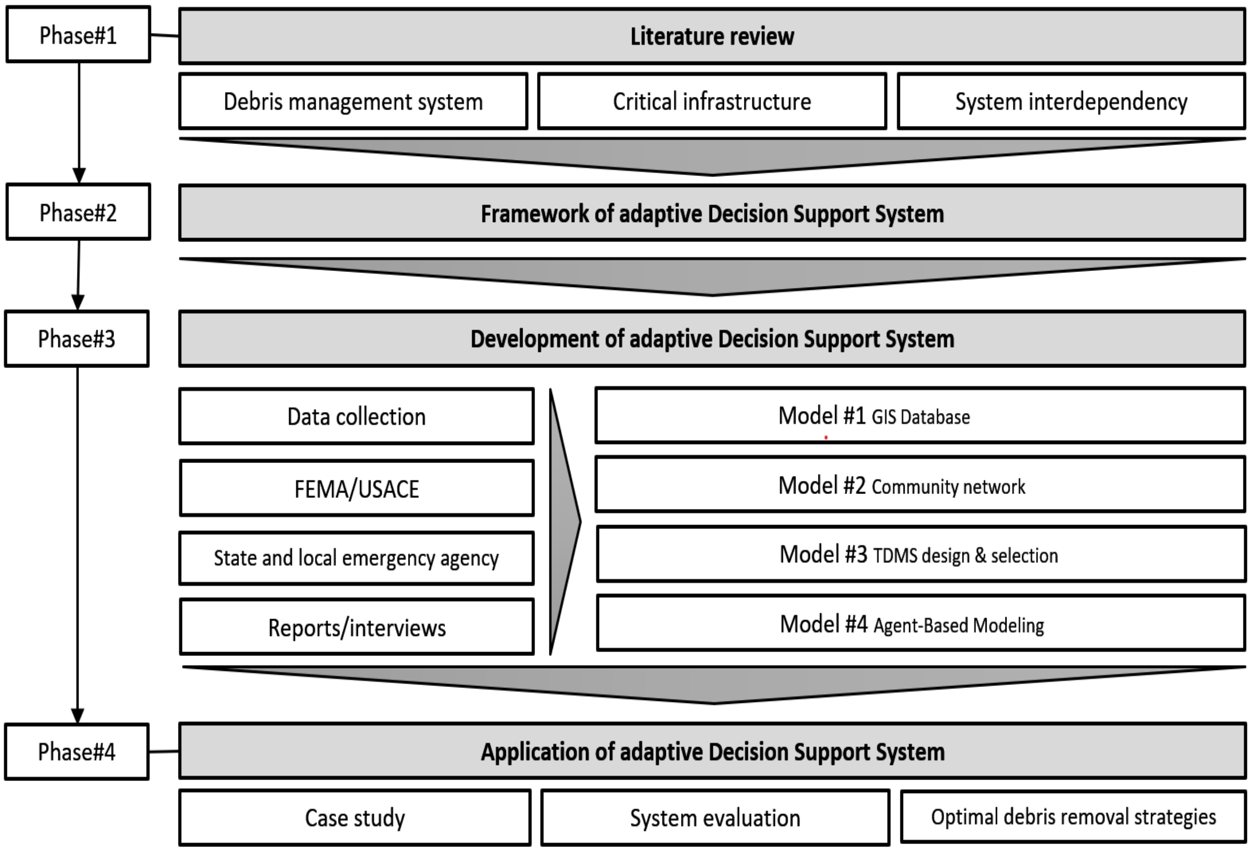


Figure 3-1 Research methodology framework

3.2 Research methodology framework

3.2.1 Phase 1: Literature review

A systematic and comprehensive literature review is critical to gain a good understanding of the complexity of disaster debris management systems, including debris cleanup processes, required facilities and resources to transport debris, impacts of infrastructure capacity and serviceability on the debris removal performance. This requires data/surveys/interviews to conceptualize and construct an effective debris management system and model the system. The literature review phase of this study addressed three main areas: disaster debris management systems, the inter-relationship between critical infrastructure and debris management systems, and system modeling for debris management (see Table 3-1).

Table 3-1 Three main areas and specific topics in the literature

Area	**Topics**
Disaster debris management	Debris removal process; type of debris; debris collection and treatment options; temporary debris management sites; general issues during debris removal; factor analysis for debris/waste collection performance.
Critical infrastructure	Type of critical infrastructure affecting debris removal such as civil, civic, and social infrastructure; inter-relationship between infrastructure.
System modeling	Complex systems; complex system modeling and methodologies; simulations, including discrete events, system dynamics, and agent-based modeling.

As further discussed in Chapter 2, there are few research articles and relevant data in the area of disaster debris management. Thus, efforts of this study were mostly focused on collecting and summarizing post-disaster after-action reports published by U.S. state and local agencies, documents on FEMA's debris removal planning and practices, news articles about debris management during and after disasters, and interviews with officers in emergency agencies. To examine the inter-relationship between the serviceability/capacity of critical infrastructure and debris removal performance, this study examined past debris removal practices and articles in the field of solid waste management. The comprehensive literature review clearly identified state of the art within the field and gaps in knowledge in the domain of disaster debris management. The findings strongly support the point of departure of this study, the research methodologies used, and the framework developed.

3.2.2 Phase 2: Framework for the adaptive decision support system

Based on the comprehensive literature review on 1) disaster debris management systems, 2) the roles of critical infrastructure and 3) system modeling methods, this study developed a framework for an adaptive decision support system for effective disaster debris management. The framework consists of four modules: (i) GIS database, (ii) community structure analysis, (iii) temporary debris management site (TDMS) network design and selection, and (iv) resource allocation and routing.

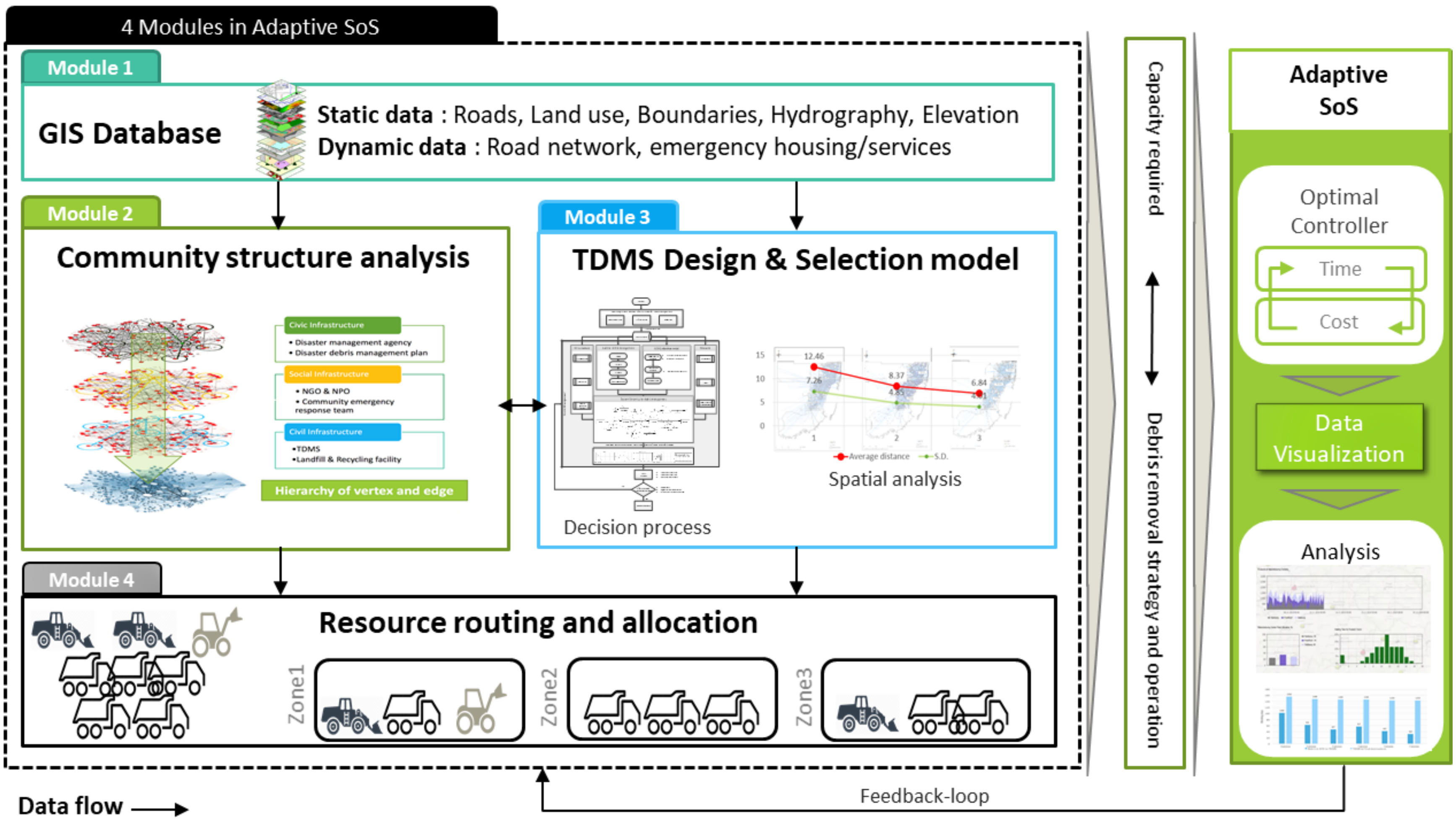


Figure 3-2 Framework of the adaptive decision support system

Note: Adaptive DSS consists of four core modules: Modules#1-4.

Module#1 was designed to provide the required information/data for Modules#2-4, such as the amount/location of debris generated, serviceability of road networks, community zoning systems, and waste-related facilities. Module#2 analyzed community centrality based on the layout of the road network, census blocks, and debris generated. These analyses supported the identification of optimal locations for TDMSs in Module#3 and allowed prioritization of debris cleanup zones in Module#4. In Module#3, TDMS design and selection model was designed to identify feasible locations for installing TDMSs based on three types of decision parameters, namely technical, environmental, and social perspectives. Agent-based modeling (ABM) was applied in Module#4 to understand the complex behaviors of debris management systems and optimize such systems for multiple scenarios. The simulation results can be reported to decision makers for better understanding and to support decision making. Any uncertainties during/after disasters will be effortlessly reflected in modules in the framework. This will improve the prediction of debris removal performance and support optimal solutions within the existing serviceability of critical infrastructure and the locations/amount of debris generated.

3.2.3 Phase 3: Development of the adaptive decision support system

3.2.3.1 Module 1: GIS database

A database is a critical component for disaster debris management systems, and it is mainly used to store and retrieve data/information required for debris removal planning and operations. In debris management, most of the required data are spatial data such as the location of debris generated, location of debris treatment facilities, and road networks. These heterogeneous spatial data include points, lines, and polygons and can thus be managed in a GIS spatial database. Further, multiple agencies, including USGS, FEMA, and state- and local-level emergency agencies, provide GIS data during and after disasters that provide information about debris generated, road network serviceability, and the status of debris cleanup. Thus, a GIS database is a feasible data management method to store and retrieve debris-related data as well as update critical data in real-time after disasters such as that pertaining to road traffic and blockages and other emergent dynamics during debris removal operations. Table 3-2 outlines the data applied to the adaptive decision support system developed in this study.

Table 3-2 Spatial data type and sources

	Data type	Sources
Debris	Amount; density (locations); existing debris removal plan and operation system	FEMA's Hazus-MH; City of Baton Rouge; Local news articles
GIS Data	Drainage and flood zones; road network; city zoning (e.g., commercial and residential); location of facilities, including schools, hospitals, governmental agencies, landfills, TDMSs, temporary medical services, and evacuation centers	EBRGIS; interview
Resources	Trucks; loaders; chippers	City of Baton Rouge LDEQ

Note:All data used in the study is open to the public.

Two types of data are stored in a GIS database: static and dynamic data (see Figure 3-3). Static data is defined as data that does not change over time and/or after being recorded. Dynamic data is defined as data that may change over time and is continually updated. In the context of disaster debris management, static data includes the road network, locations of waste-related facilities, and community zoning (e.g., residential, commercial, and industrial zoned properties). These data can be obtained from the USGS, EPA, or GIS databases operated by the state- and city-level governmental agencies. Dynamic data includes data generated or updated during and after a catastrophic event, such as the amount of debris generated, debris locations, road network blockages, and capacity and serviceability of waste-related facilities. These data can be obtained from Google Crisis Response, city emergency agencies, and non-governmental organizations (NGOs). The GIS database establishes a channel to provide this spatial data/information for Modules#2-4.

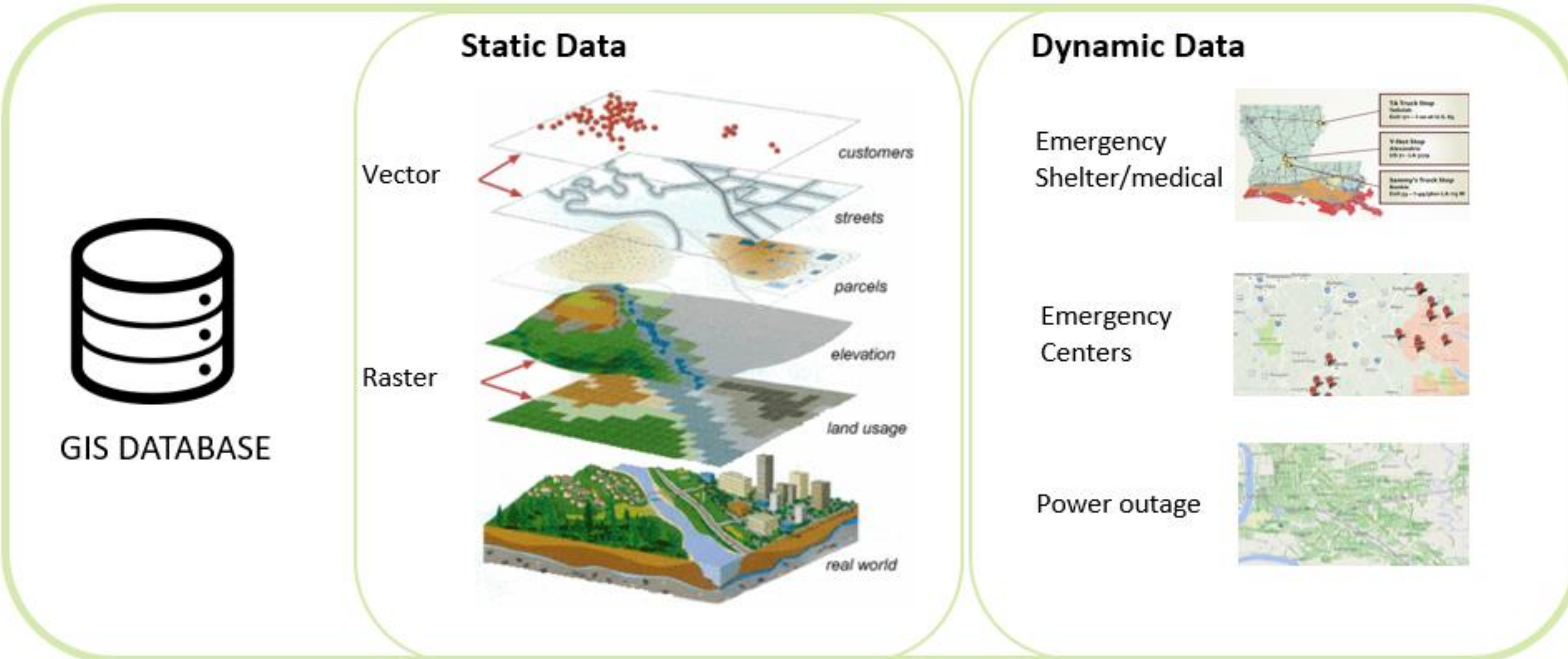


Figure 3-3 Types of data in a GIS database: Static and dynamic data

3.2.3.2 Module 2: Community structure analysis

During debris removal, it is critical to prioritize debris cleanup zones to enhance the overall debris removal process and disaster recovery performance in general. For example, debris removal on a highway significantly improves road network serviceability, in contrast to debris removal on local roads that are used by few drivers on a daily basis. To quantify urban network centrality, this study examined multiple prior studies that have established methods to measure spatial network characteristics and urban phenomena in terms of the importance of particular junctions, the connectedness of rooms in buildings, pedestrian traffic in a city, and the distribution of retail and service establishments (see Table 3-3).

Table 3-3 Summary of urban network studies

Topics	References
Importance of particular junctions in transportation networks	(Garrison, 1960; Garrison and Marble, 1962; Kansky, 1963; Haggett and Chorley, 1969)
Flow of pedestrian traffic on street	(Hillier et al., 1987)
Distributions of retail and service establishments in urban environments	(Porta et al., 2005; Sevtsuk, 2010)

The network centrality in Table 3-3 was calculated using two types of network elements: nodes and edges. Several toolboxes are available for spatial network analysis, such as Axwoman, SANET, MoSC, and Urban network analysis. In this study, we utilized Urban Network Analysis developed by MIT City Form Lab (http://cityform.mit.edu) as it can be used in the GIS platform and ArcGIS toolbox and can measure five types of centralities, namely reach, gravity, betweenness, closeness, and straightness (Sevtsuk and Mekonnen 2012). Using Urban Network Analysis, this study identified community zones with higher centrality and betweenness. These measurements were applied to Modules#3 and #4 to identify optimal TDMS locations and to Module#4 to prioritize debris removal zones.

3.2.3.3 Module 3: TDMS selection and network design modeling

TDMSs play a critical role in debris management. Most of the debris generated is transported to a TDMS, where it is chipped, ground or burned before being transported to final destinations such as landfills or recycling facilities. While the installation of TDMSs has multiple positive impacts on debris removal performance, multiple issues have been reported during their operation in the United States, such as noise, odors, and heavy traffic near such facilities. However, most studies have focused on either land suitability analysis based on existing policies and regulations or technical performance. There is a lack of research integrating the multiple factors required before and during TDMS operation to identify the optimal location of TDMSs. Based on the broad literature review on policies, regulations, and after-action reports related to TDMSs in Chapter 2, this study defines three performance parameters for quantification: technical, environmental, and social performance.

<u>Technical performance (P_T)</u>: Engineering design is defined as a systematic approach to generate, evaluate, and specify system elements for designed or requested objectives under the consideration of certain constraints and requirements (Dym et al. 2005). Technical performance is defined as the measured engineering performance due to the spatial characteristics of a TDMS location. To quantify technical performance, Kim (2014) developed a mathematical model to identify the optimal location for a TDMS and minimize the total distance from debris generated to assigned TDMS locations; $I \text{ and } J$ is a set of debris pickup locations and TDMS candidate locations respectively. Constraints are not described in the simplified model below.

$$\textit{Optimal TDMS location} = \textit{Min} \sum_{i=1,j=1}^{n,m} D_i \, T_j \qquad \forall i \in I, \forall j \in J$$

D_iT_j: *Distance from* D_i to T_j

D_i: *Collection point of debris generated at location i*

T_j: *TDMS candidate at location j*

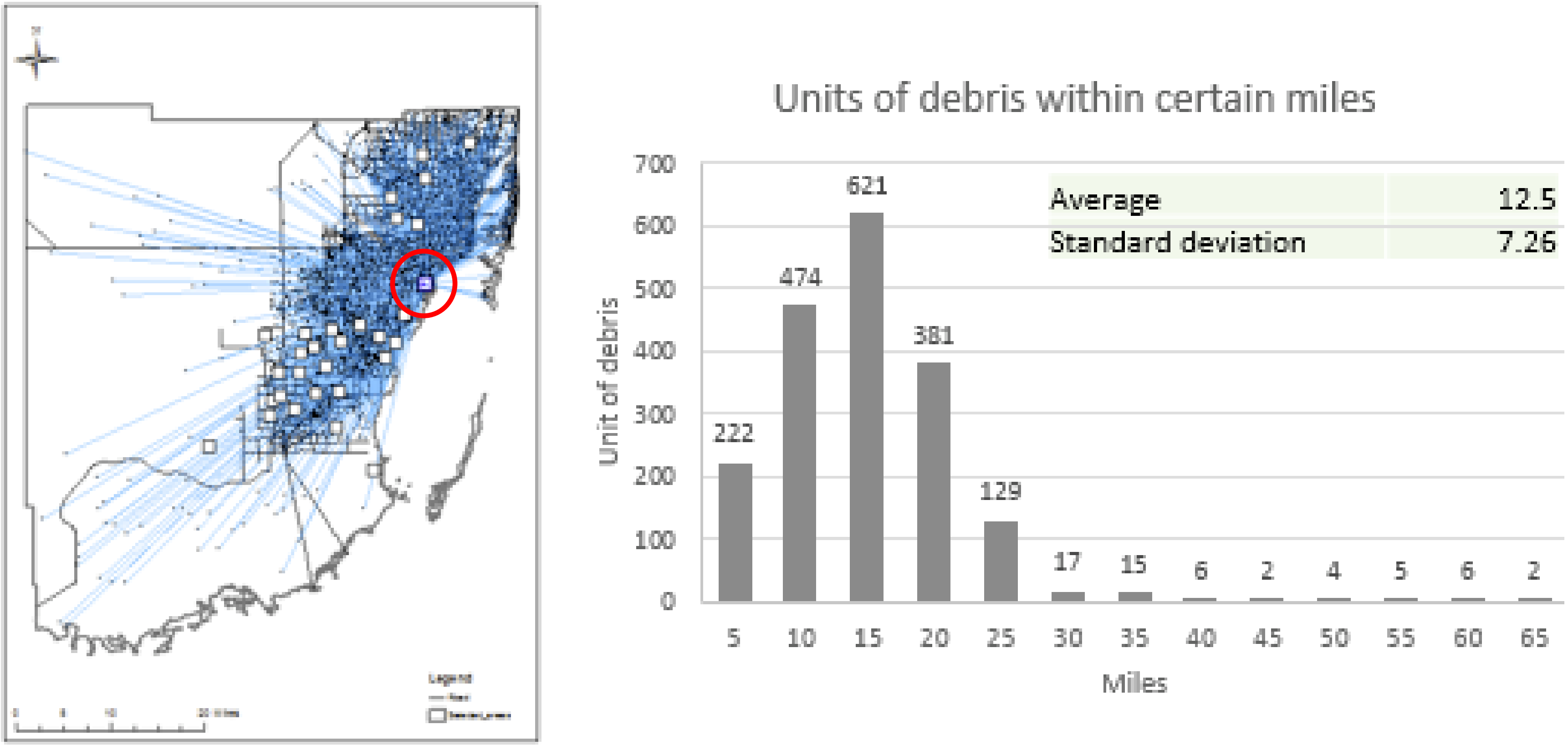


Figure 3-4 Results of the TDMS design and selection model

Note: small boxes on the left refer to TDMS candidate locations. The box with the blue star (in the red circle) is identified as an optimal TDMS location to minimize the total debris transporting distances (basic assumption: debris must be hauled from debris pickup locations to an assigned TDMS).

As shown in Figure 3-4, the model was able to identify the optimal location of a TDMS among multiple TDMS candidate locations. Based on the debris pickup sites and selected TDMS location, decision makers can perform statistical analysis to determine TDMS input and output capacity.

Environmental performance (P_E): Certain debris streams may pose a risk when it is cumulated, staged, and stored in larger quantities to human health. Thus, it is critical to locate TDMSs to prevent any possible environmental contamination or pollution during and after TDMS operation. For example, piles of scrap tires are a potential fire hazard and can attract disease vectors (U.S. EPA 2019). After a disaster, scrap tires may provide a breeding habitat for insects like mosquitoes. Most state- and local-level debris management planning is based on the EPA's *Planning for Natural Disaster Debris* (U.S. EPA 2019). In this study, the environmental performance is designed to measure the existing and emergent regulatory performance of different areas zone based on the EPA's guidelines. The following list summarizes the EPA's guidelines (U.S. EPA 2019).

i. *Sufficient size on appropriate topography and soil type*
ii. *Certain distances from potable water wells, rivers, lakes, and streams*
iii. *Not be established in/near the areas of 100 year floodplain and wetland*
iv. *Control systems to mitigate stormwater runoff, fires, and dust.*
v. *Free from any obstructions (e.g., power lines and underground pipelines)*
vi. *Accessible to heavy and large equipment during operation*

Social performance (P_S): Radius distance (i.e., Euclidian distance) from a TDMS location to residential areas was measured. While a TDMS operation has multiple positive impacts on debris management, several social issues regarding TDMS operation have been reported. For example, a TDMS can 1) attract vectors such as rodents and other pests, 2) generate noise and odors at certain levels considered unacceptable by residents nearby, and 3) increase traffic around TDMSs.

3.2.3.4 Module 4: System simulation by agent-based modeling

Module#4 was designed to simulate debris cleanup operations based on the results of the previous modules (#1-3). This included routing and resource allocation (e.g., loaders and trucks) to assess debris removal operations. In simulation experiments, a decision maker can evaluate the efficiency of existing or newly adjusted debris cleanup operation strategies based on the dynamic, emergent environment after a disaster. For example, the collapse of a bridge may require the relocation of a TDMS, which can significantly affect the overall performance of existing debris removal. Module#4 enables decision makers to adapt easily to a dynamic environment after a disaster by evaluating the performance of multiple debris management scenarios over time.

Module#4 employed agent-based modeling. ABM is a class of computational models for simulating the actions and interactions of autonomous agents, including both individual and collective entities, with a view to assessing their effects on a system as a whole (see Figure 3-5). The purpose of ABM is to search for explanatory insights into the collective behavior of agents obeying simple rules in natural systems and engineering problems (Borshchev and Filippov 2004).

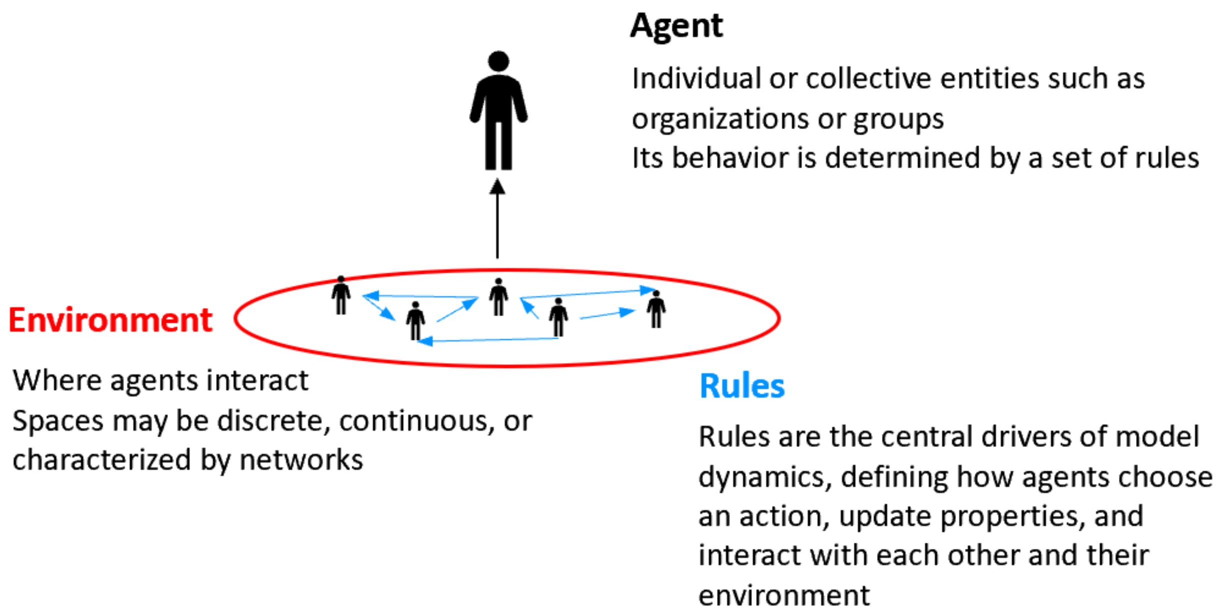


Figure 3-5 Three critical elements of ABM

Note: The elements of the ABM model are defined based on Epstein and Axtell (1996) and Macal and North (2010), as: (i) a set of agents: resources such as equipment, their attributes and behaviors, (ii) a set of agent relationships and methods of interaction: an underlying topology of connectedness defines how and with whom agents interact, and (iii) the agents' environment: agents interact with their environment in addition to other agents.

Simulations including discrete events, system dynamics, and ABM have been widely used in the field of disaster management as part of decision support systems. Fiedrich and Burghardt (2007) applied ABM to support numerous processes throughout different phases of the disaster management cycle, from mitigation and preparation to actual response and recovery. Several studies have focused on crossing the boundary between generic research on agents and possible applications in the domain of disaster management such as Robocup Rescue (Kitano and Tadokoro 2001), Combined Systems (Veelen et al. 2006), Aladdin (Jennings et al. 2006), EQ-Rescue (Fiedrich 2006), and FireGrid/I-Rescue (Tate 2006). Wagner and Agrawal (2014) investigated crowd evacuation modeling using ABM. This allowed for multiple scenario testing and decision support for the planning and preparedness phase of emergency management regarding fire disasters at concert venues. Tan et al. (2015) also developed an agent-based simulation by combining human behavior with predictable spatial accessibility in a fire emergency. Wang et al. (2016) used Netlogo for multimodal evacuation simulation of a near-field tsunami to identify impacts of varying decision time on the mortality rate, different means of transportation, and vertical evacuation gates on the estimation of casualties. Kim et al. (2018) applied system dynamics to analyze the patterns of disaster debris removal based on multiple scenarios.Table 3-4 compares discrete event, system dynamics, and agent-based models.

Table 3-4 Comparison of three simulation methods: SD, DE and ABM

	System dynamics (SD)	Discrete Event (DE)	Agent-Based Model (ABM)
Feature	- Used to gain greater understanding of long-term system behavior and dynamic feedback behavior - Focus on flow of systems in different scenarios - Mostly used in policy making - Used at the strategy level	- Used to enact a system that with a queue network and to compare and predict scenarios - Focus on processes that involve the use of queues - Mostly used in decision and prediction making - Used at the operational/tactical level - Top-down approach	-Used to identify the interactions and operations among entities in realistic and flexible ways -Focus on the interactions that occur in systems -Mostly used in business areas - Bottom-up approach
Advantages	- Helps understand complex systems - Identifies the relevant factors that exist in complex systems - Scenario testing can be modified to get different results	-Easy for users to understand with the help of animations and graphics built into the software package -Has unlimited flexibility to determine the behavior of entities - Straightforward modeling once the problem has been clearly defined	-Can capture emerging phenomena -Flexible to use -Can describe a system in terms of actual scenarios
Disadvantages	-Big systems may be too complex for the modeler to understand -Failure to identify problems may cause failure when implementing a system dynamics approach	-Less effective in showing the impacts of variability -Not suitable for use in modeling related to human behavior	-Involves highly skilled computation for use in large systems -Involves significant costs for communication

Reference: (Borshchev and Filippov 2004; Sumari and Ibrahim 2013)

3.2.4 Phase 4: Applications of the adaptive decision support system

The adaptive decision support system developed using GIS-based ABM can be applied in many ways. Major parameters of analysis are operation time and cost. As debris management is a part of disaster management, it is critical for predicting the time and cost to clean up debris generated by a disaster. This information is critical not only for emergency management teams but also for other disaster-related agencies and affected residents. Further, the rate of debris removal in areas over time is important to prepare for disaster recovery processes after debris removal. Finally, debris removal monitoring based on simulation facilitates the communication of emergent results to assist the development of alternatives and gauging the efficiency of the debris removal process.

Figure 3-6 describes the structure of the adaptive decision support system. The environment was developed by information and data retrieved from Modules#1-3. The decision space enables users to apply multiple rules and scenarios using agents such as regulations and policies. Based on environment and rules settings, agents continually interact with each other until a designed time or rule. All agents' movements and interactions are stored, analyzed, and visualized in real time.

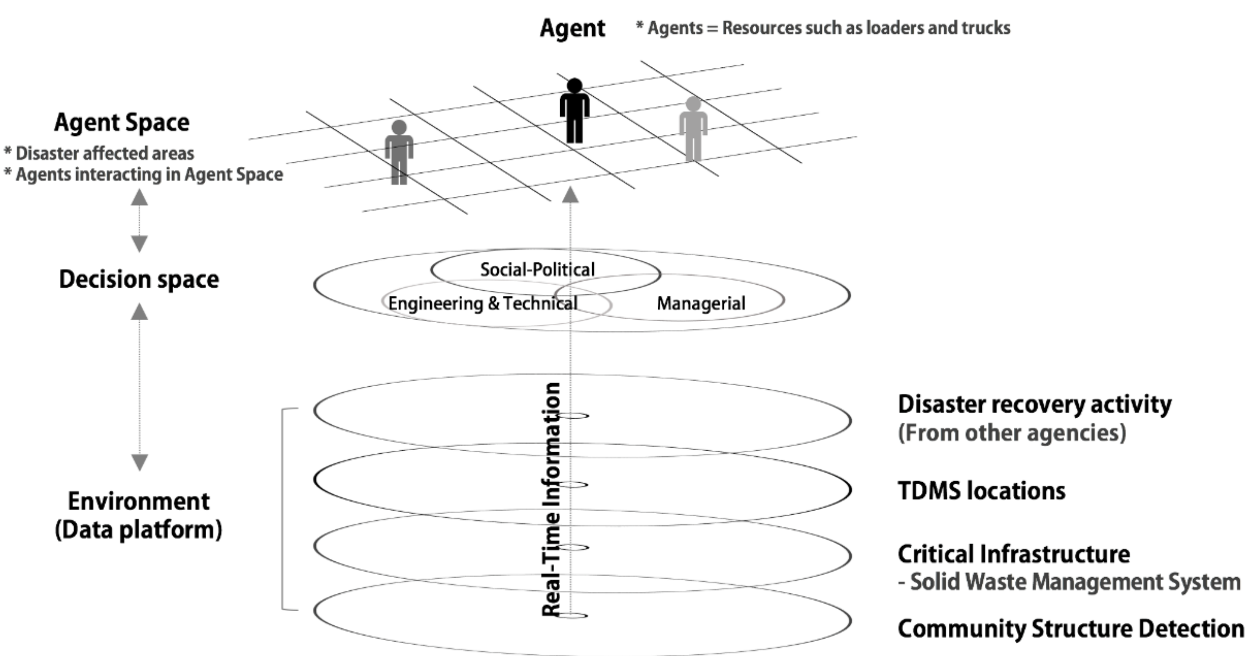


Figure 3-6 Structure of the adaptive decision support system

3.2.4.1 Debris removal zone hierarchy

Using the community network analysis in Module#2, the adaptive decision support system can analyze debris removal start/finish time (date) for different zones (see Figure 3-7). This supports decision makers in focusing their efforts and resources on critical zones in an emergency. It also enables other emergency agencies to coordinate their operation plans based on debris removal schedules.

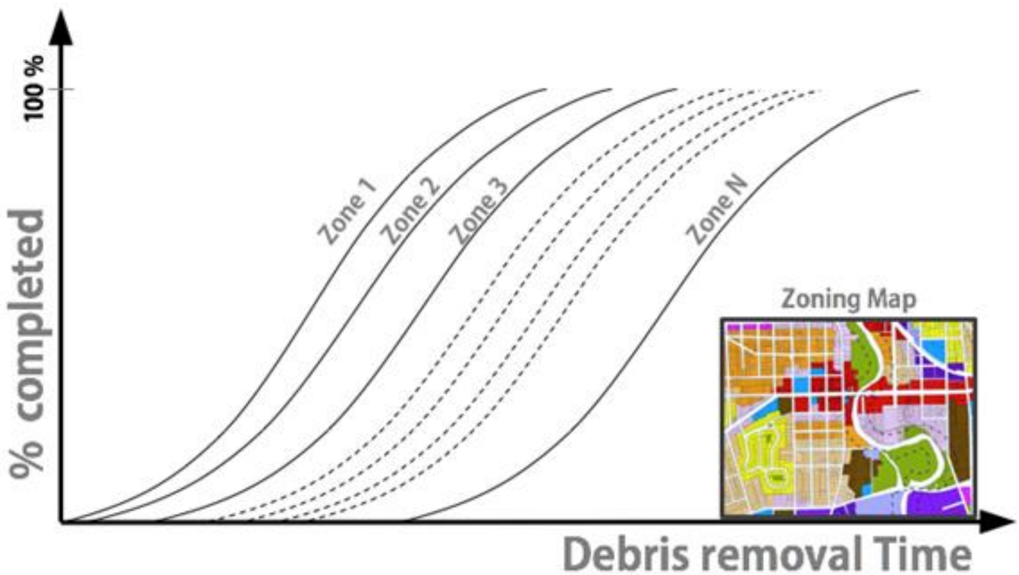


Figure 3-7 Debris removal time for different zones

3.2.4.2 Infrastructure and resource utilization assessment

The adaptive decision support system assesses the capacity of resources and infrastructure needed to clean up debris generated within a designated time and budget. It further analyzes daily and weekly performance dynamics of debris removal, TDMSs, and final destinations over time. These analyses support the development of effective debris removal operation strategies over time. Figure 3-8 describes the types of assessments and associated variables.

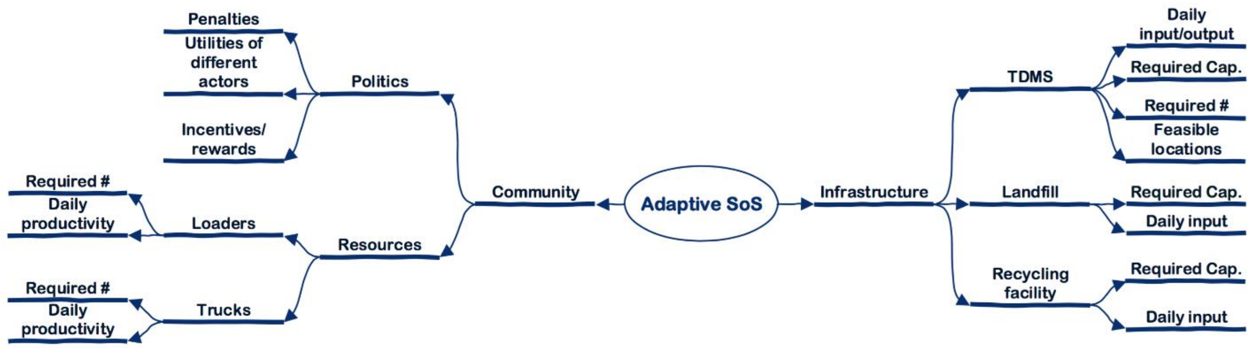


Figure 3-8 Types of assessments in the adaptive decision support system.

3.2.4.3 Debris removal cost-benefit analysis and visualization

There is a trade-off between debris removal time and cost. Adaptive SoS identifies optimal solutions based on a given time and cost. Time and cost metrics, as controllers in the ABM, allow the selection of priorities and the comparison of optimal solutions, considering different social and political scenarios. A decision maker then selects an optimal solution based on various alternative scenarios (see Figure 3-9).

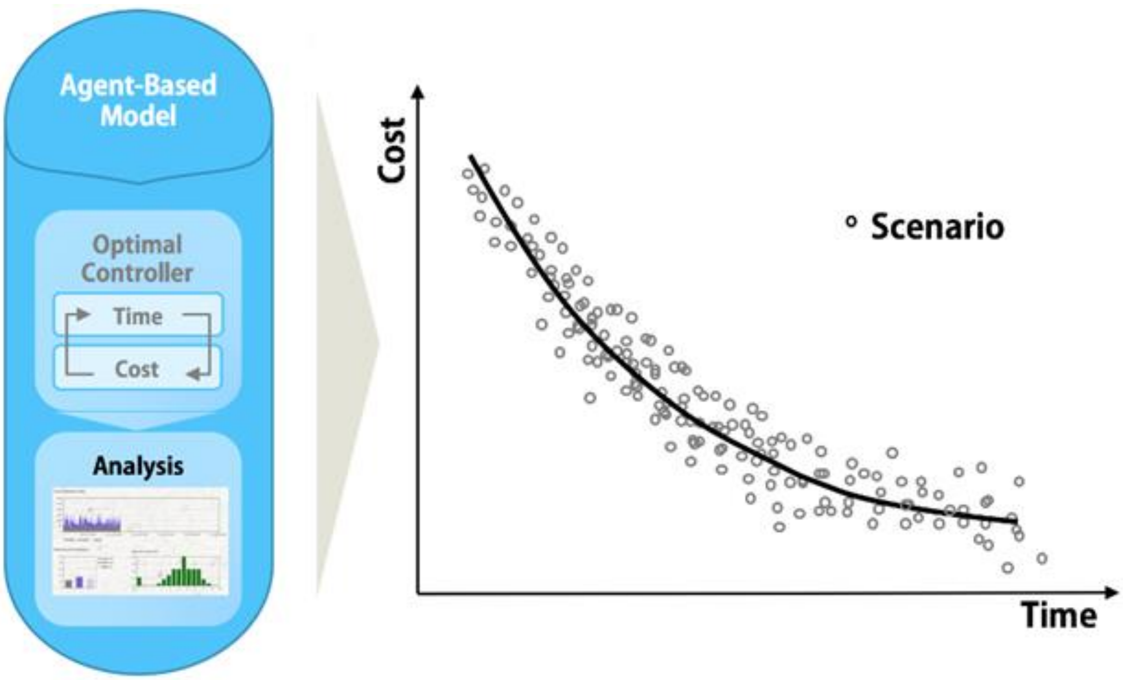


Figure 3-9 Time-cost analysis for alternative debris removal scenarios

Further, the proposed decision support system combines geospatial mapping of potential TDMS locations with summaries and charts exploring tradeoffs between output metrics such as cost, recovery time, and social acceptability. Statistical clustering analysis techniques were used in accordance with robust decision-making principles to identify strong TDMS locations and debris removal strategies (Groves and Lempert 2007; Lempert et al. 2006). Here, robust solutions are those that are high performing not only across a wide range of uncertain disaster scenarios but also across preferences in terms of cost and time tradeoffs and differences in the degree to which technical, managerial, and socio-political considerations are prioritized.

3.2.4.4 Monitoring debris removal operations using a visualized GIS platform

Monitoring debris removal performance is critical to bridging the gap between a plan and its implementation and operation. This enables decision makers to compare the expected amount of debris at a certain time with the actual amount of debris (green line) in a community (see Figure 3-10). This supports emergency agencies in identifying current bottlenecks of the system and determine the need for alternative resource allocation and additional infrastructure and resources to expedite debris removal.

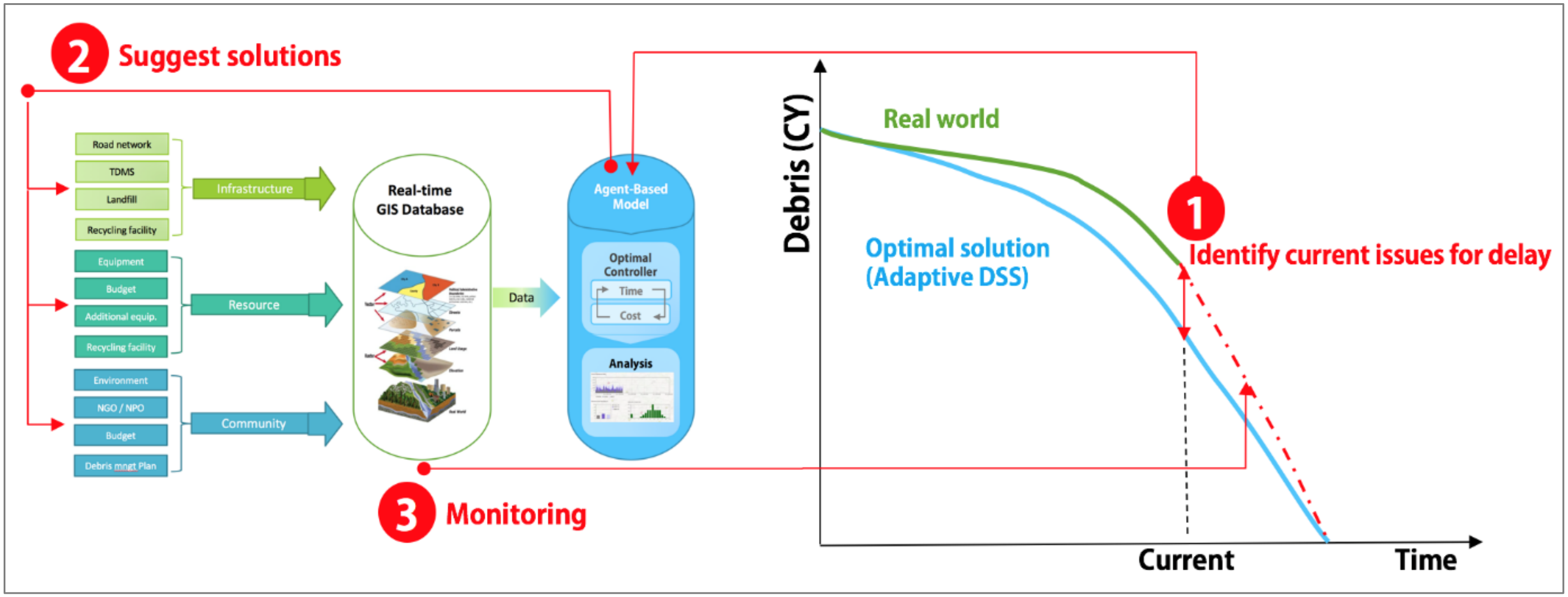


Figure 3-10 Debris management performance monitoring and feedback loop

Previous research has highlighted the importance of sharing and coordinating information between disaster relief agencies (Bharosa et al. 2010; Kim et al. 2013, 2018b; Simon et al. 2015). The adaptive decision support system developed with a GIS platform interactively provides multi-level information/data to users.

3.3 Expected results

This chapter discussed the research methodology, framework, and an adaptive decision support system for effective decision making and transformed it into a more engaged process that covers mitigation and preparedness of response and recovery activities. The expected outcomes of this study are:

- Develop a framework for post-disaster debris management based on the concept of system of systems,
- Identify a network of interdependent infrastructure systems that influence debris removal within a community and their relative importance,
- Develop a real-time GIS database to integrate the data associated with 1 and 2 above and make it available for analysis of the remaining objectives,
- Model the selection/design of a TDMS network, including: (1) geographical characteristics (GIS data) and interdependent infrastructure as identified in 1 and 2 above and (2) availability of resources for debris removal,
- Simulate the productivity of debris management using real-time GIS data to gain insights on the impacts of the dynamic nature of a disaster-affected area,
- Develop a visual, interactive GIS-based simulation platform for effective coordination among agencies and monitoring of on-going debris removal operations under dynamic conditions, and
- Establish a feedback loop to incorporate real-time data on debris removal operations in the simulation model for updating corresponding disaster management activities.

3.4 Conclusion

This chapter discussed the research methodology, framework, and applications of an adaptive decision support system for effective decision making and monitoring of a debris management system over time. When developing the adaptive decision support system for effective decision making in the uncertainty of a disaster and its impacts, it is critical to understand the characteristics of debris management and its inter-relationship with critical infrastructure. Thus, this study conducts a systemic review of disaster debris management systems, including the entire debris management process, related critical infrastructure for debris removal, and complex system modeling.

Increasing the understanding of emergency operations at the nexus of the community, infrastructure, and the environment: Interactional elements cover broad concepts that can be added to policy making, such as economic, environmental, social-political-institutional, as well as engineering-technical aspects. Integrating all factors within one framework along with a real-time simulation of the process will help emergency agencies to develop strategies at the nexus of the communities, infrastructure, and the environment while they uncover emergent dynamics. The proposed model aims to reflect the complexity of this nexus within the model and its simulation. The methodology consists of four phases: a literature review, the framework of the adaptive decision support system, development of the system, and its application. To manage city- or state-level spatial data, a GIS database was utilized to store, retrieve, and update data before and after a disaster. To analyze community centrality and optimal TDMS locations, GIS-based spatial analysis methods were applied and developed. Beyond an engineering approach to identify TDMS locations, this study defined three performance measures—technical, environmental, and social measures—to meet the needs of entities that include emergency agencies, environmental agencies, and residents in an affected community. Finally, to develop a simulation model for debris management, three simulation methods were discussed in this chapter, namely discrete events, system dynamics, and ABM. The three elements of ABM were discussed in terms of how they were used to develop a simulation model.

The following chapters discuss the methodology for each module in detail. Chapter 4 discusses data visualization for decision making, and Chapter 5 applies the proposed adaptive decision support system in a case study—debris management in the city of Baton Rouge after the 2016 Louisiana flood.

CHAPTER 4. DEVELOPMNET OF ADAPTIVE DECISION SUPPORT SYSTEM

4.1 Introduction

Complex post-disaster debris management problems require a research methodology that integrates multiple models and methods. As further discussed in Chapter 3, this study applied multiple models and methods to integrate numerous community characteristics and environments regarding civil, civic, environmental and social infrastructure and to develop an adaptive decision support system.

This study defined the proposed decision support system for an effective debris management system as an adaptive decision support system. In the previous studies, an adaptive decision support system was defined as a system that is able to adapt dynamic circumstances to support (1) decision maker's needs, (2) the problem, and (3) the decision context (Druzdzel and Flynn 2002; Fazlollahi et al. 1997). The effectiveness of decision support system (DSS) for debris management can be enhanced through dynamic adaptation of circumstances affected by a catastrophic event. In a pre-disaster scenario, the adaptive DSS runs a simulation experiment based on the given conditions and data (e.g., debris estimation from FEMA's Hazus-MH, road network status from the previous flood inundated areas, available equipment). Thus, a result of simulation includes a certain level of uncertainty. Comparing to simulation experiemnts in a pre-disaster scenario, the performance of the adaptive DSS in a post-disaster scenario can be enhanced by up-to-date geospatial data and information from Module#1. For example, it can reflect the exact amount of debris on curbside from field surveys as well as the real-time road network serviceability to transport debris on a curbside to TDMSs. As the proposed DSS can adapt these post-disaster circumstances into a simulation experiment, this study defined the proposed DSS as an adaptive decision support system.

This chapter discusses the four core modules of the adaptive decision support system, namely the GIS database, community network structure analysis, spatial data analytics and optimization for TDMS design and selection, and agent-based modeling for system simulation and optimization (see Figure 4-1).

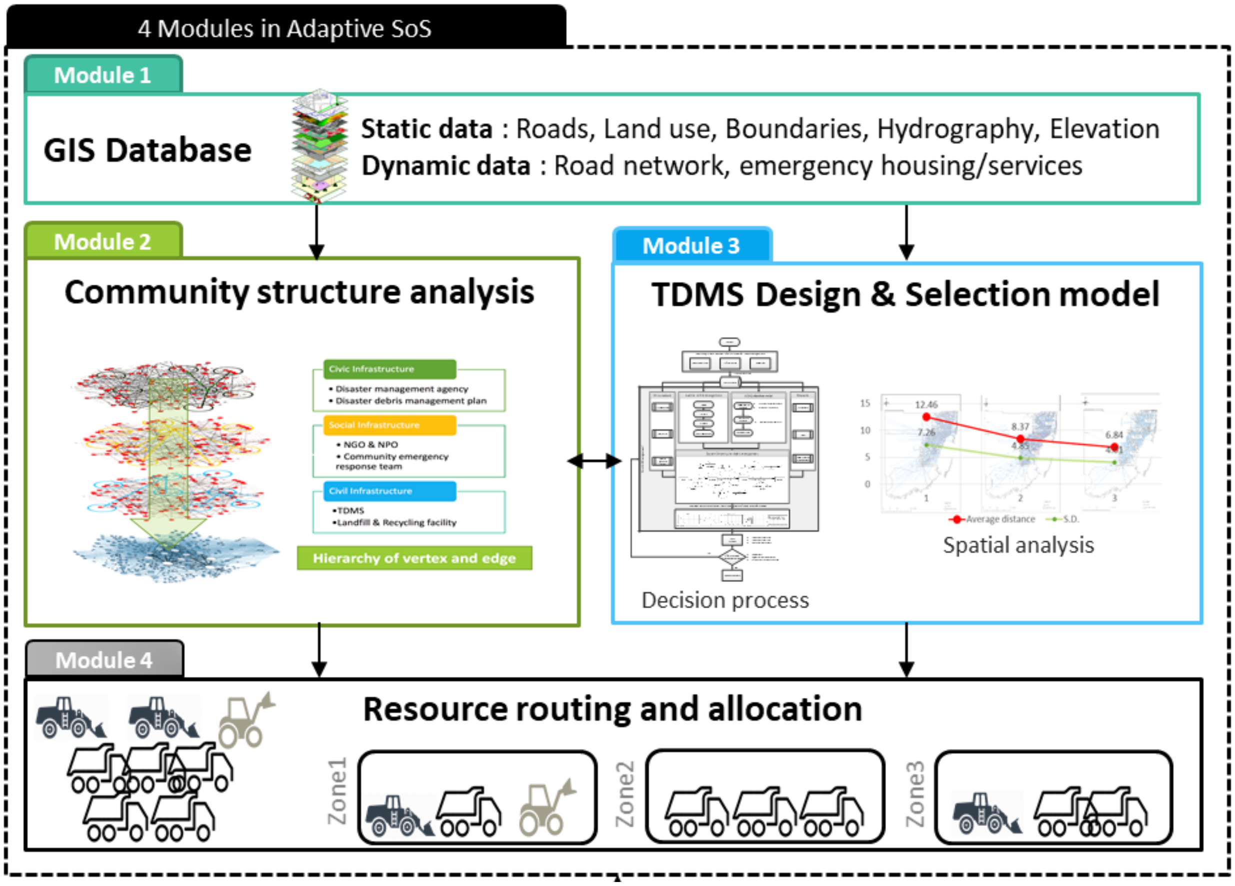


Figure 4-1 The four core modules of the adaptive decision support system

The main functions of the adaptive decision support system are to (1) provide critical information/data related to disaster debris management in a visualized GIS platform, (2) identify feasible locations of TDMS, (3) perform system performance analytics and optimization, and (4) visualize data analytics and simulation. The system strongly supports decision makers by helping them to understand the complexity of debris removal operations and open effective lines of communications between the involved parties. Figure 4-2 desribes the detail input and output data processing in the adaptive decision support system.

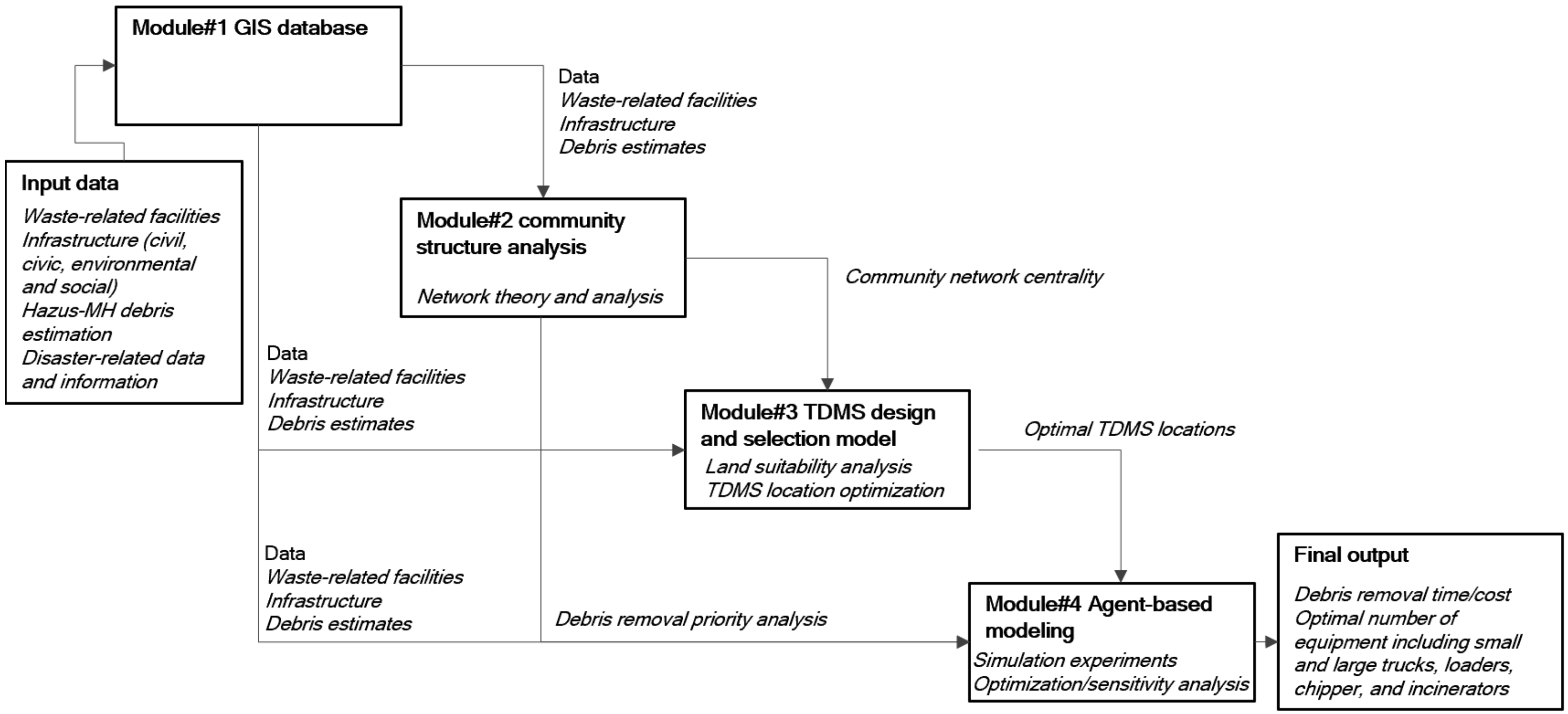


Figure 4-2 Input and output process in the adaptive decision support system

Figure 4-3 describes the detail data flow and process in the adaptive decision support system. To support multiple analysis and decision-making for an effective debris management, it consists of four modules. As the majority of methods/analysis is based on data and information acquired in Module#1, it is critical to acquire a reliable quality of data/information (i.e. data with lower uncertainty). The proposed adaptive DSS is capable of experimenting debris removal operation in a pre-disaster situation with expected disaster impacts and debris estimation from Hazus-MH. A result may contain high uncertainty because of uncertainty in multiple components such as debris locations/quantities, road network conditions, as well as the availability of pre-selected TDMSs. Thus, the adaptive DSS is able to retrieve up-to-date data and information via Module#1 (GIS database). It reflects post-disaster circumstances and impacts on a community into Modules#2-4 so that the results of simulation experiments and optimization are less uncertainty compared with results from pre-disaster scenarios.

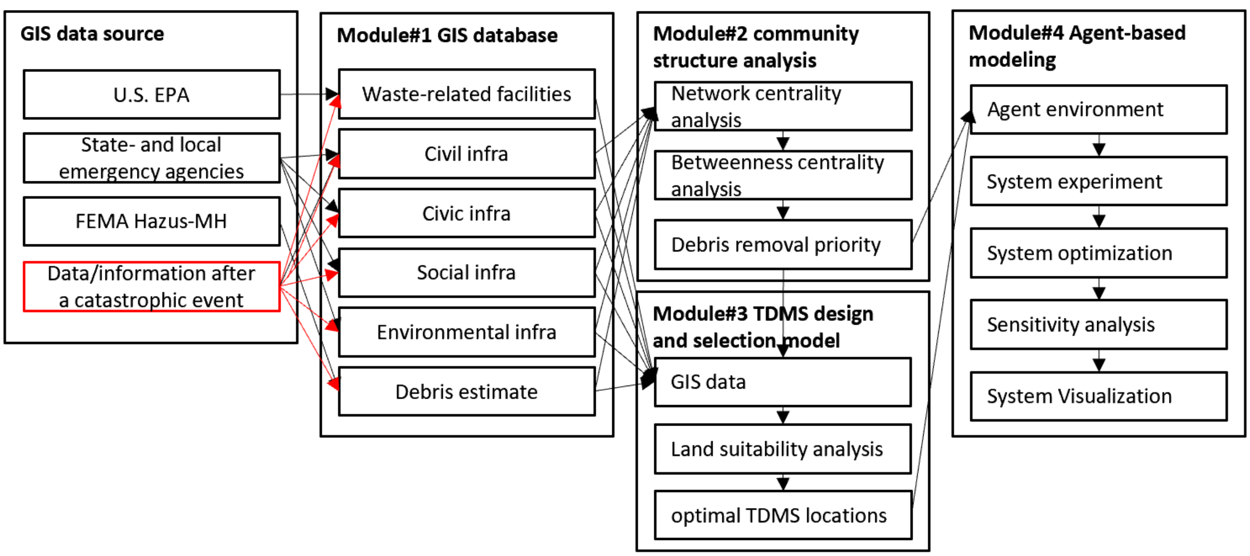


Figure 4-3 Description of data flow and process in the adaptive decision support system

Note: After a catastrophic event, up-to-date information and date are stored in Module#1 (see the red-colored box and arrows)

4.2 Core modules of the adaptive decision support system

4.2.1 Module#1: GIS database

A GIS database is a database that is optimized for storing and querying data that represents objects defined in a geometric space. Module#1 is designed to store all required and critical data related to debris management so that a channel can be established to provide the data required for Modules#2-4. There are two types of data: static and dynamic data (see Figure 4-4). Static data refers to any data published before a disaster, and dynamic data refers to emergent data published after a disaster. Most static data can be obtained from U.S. state and local agencies (e.g., USGS, U.S. EPA, and DOTs). In the case of dynamic data, there are multiple data providers (e.g., Google Crisis Response, ESRI, NASA).

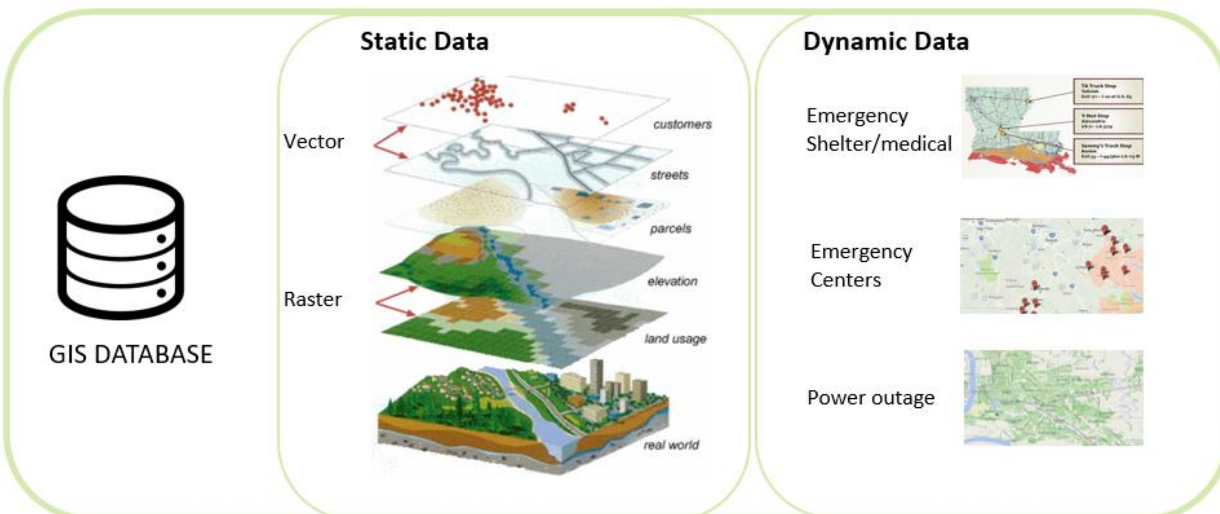


Figure 4-4 Data types in a GIS database

Static and dynamic data include vector, raster, and tables. The vector data structure is used to store spatial data that has discrete boundaries such as county borders, land parcels, and streets. These data comprise lines or arcs, defined by beginning and end points, that meet at nodes (QGIS 2009). A raster consists of a matrix of cells (pixels or grid) systematized into rows and columns such as arial and satelliate images. Each grid/cell/pixel includes a certain geospatial-related information (It can be numeric or character features):. A table in a geodatabase is also employed to store attributes, feature classes, and raster datasets.

Table 4-1 Comparison of raster and vector data

Raster	**Vector**
Raster data is generally bigger than vector data as to contain a value for each cell.	Easily overlapped with other vector data if necessary
As a raster data has its own resolution, issues may be encountered when overlaying different images.	Easier to scale and project
	much smaller file sizes comparing to raster image files
Format includes ADRG, RPF, DRG, Esri grid, and GeoTIFF	Format includes Autocad DXF, GML, GeoJSON, KML

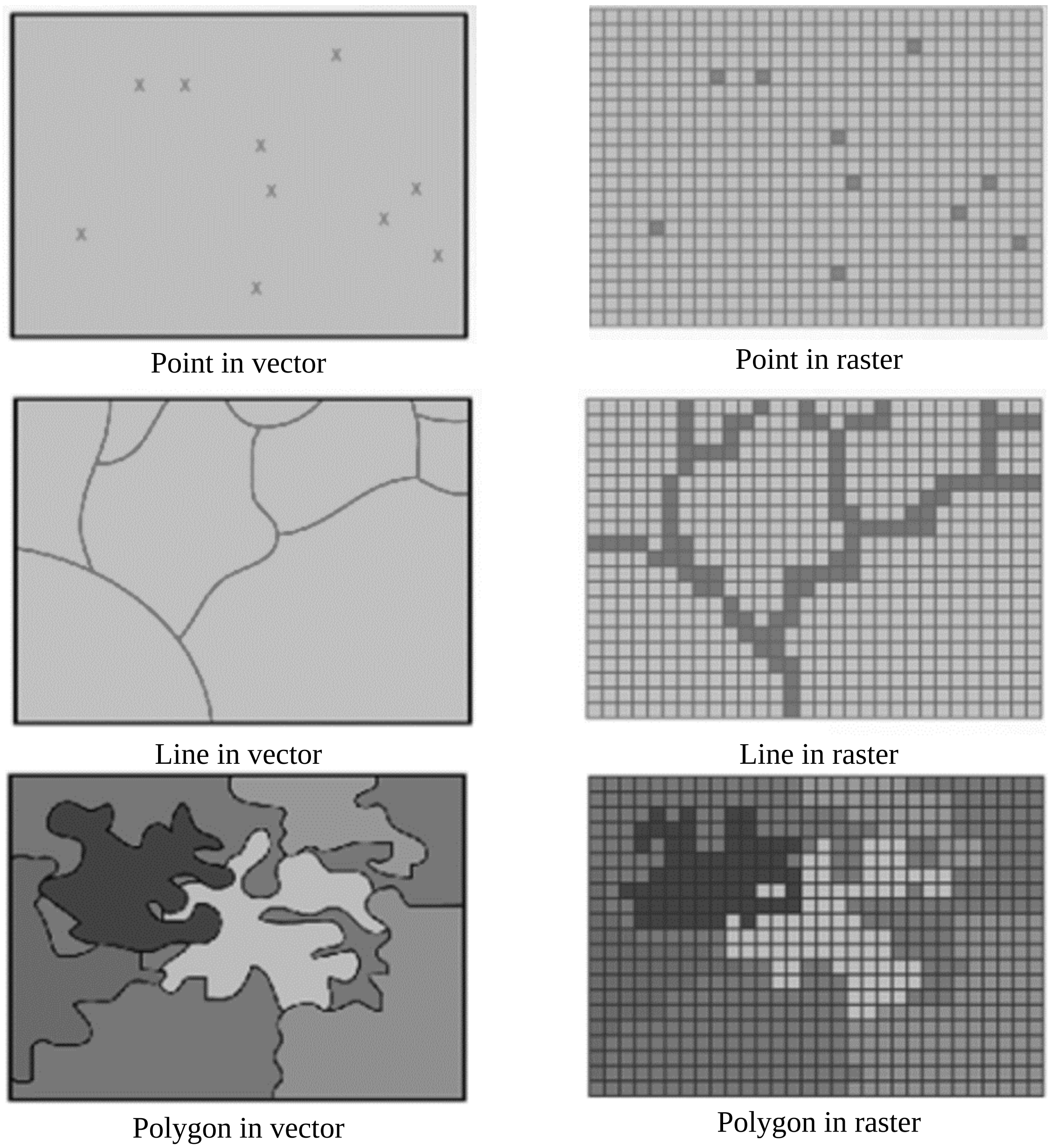
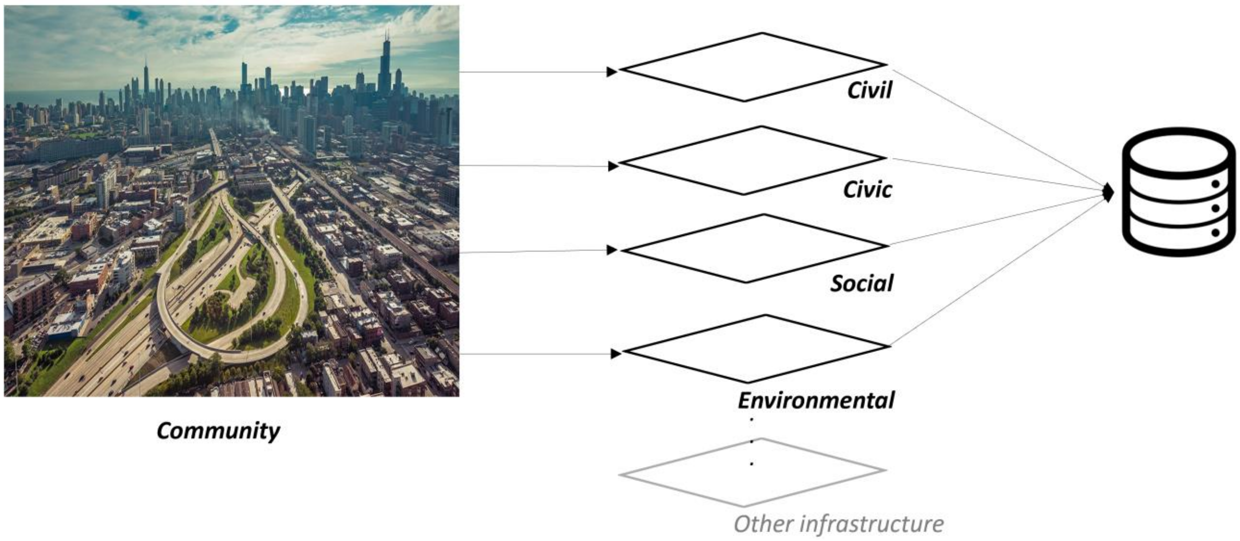


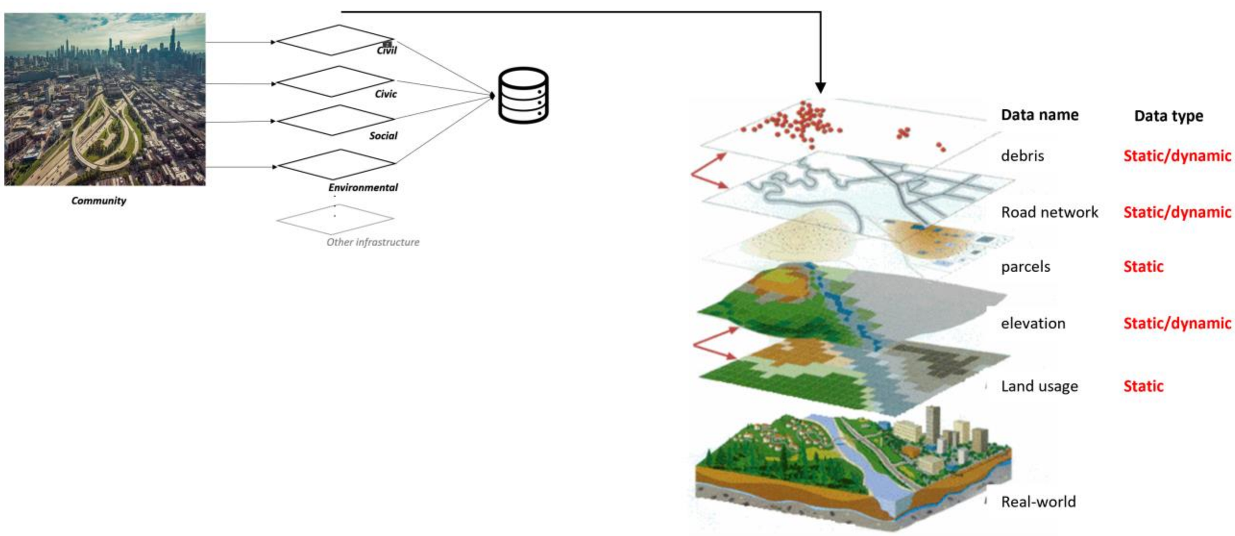
Figure 4-5 Comparison of vector and raster data

To manage data related to debris from a disaster, this study classified GIS data into four layers: civil, civic, social, and environmental infrastructure (see Figure 4-6). Civil infrastructure includes all types of physical infrastructure supporting human activities, such as roads, bridges, and waste-related facilities. Civic infrastructure is associated with spatially related regulations and policies during debris removal, such as designated areas for emergency medical and food services, governance, police and fire department. Social infrastructure refers to any facilities providing social services, such as schools, universities, churches, community center and hospitals.

Environmental infrastructure includes wetlands, rivers, lakes, soil types, and other unique environmental characteristics that should be examined before installing TDMSs.



(a) Data structure in a GIS database



(b) Data type – static and dynamic data in a GIS database

Figure 4-6 Data structure and type in the GIS database

For this study, the following data were stored in a GIS database (see Table 4-2).

Table 4-2 Spatial data type and sources

Data structure	**Data type**	**Sources**
Civil	Road network; TDMSs; landfills; recycling facilities	EBRGIS; USGS; LDEQ*
Civic	EPA policies and regulations for a TDMS; city zoning (e.g., commercial and residential);	U.S. EPA; City of Baton Rouge
Social	Schools; universities	
Environmental	Riverline; lakes; soil type; 100- and 500-year flood plains; slope	USGS; City of Baton Rouge; LDEQ
Dynamic data	Debris generated; inundated areas; emergency services	City of Baton Rouge

**LDEQ: Louisiana Department of Environmental Quality*

4.2.2 Module#2: Community structure analysis

Module#2 is designed to identify debris removal zone hierarchies in a disaster-affected community considering multiple layers of critical infrastructure (i.e., civil, civic, social and environmental) and the locations of the debris generated. To identify debris removal zone hierarchies, this study employed network theory, which is the application of graph-theoretic principles to the study of complex, dynamic interacting systems, to measure centrality (see Figure 4-7).

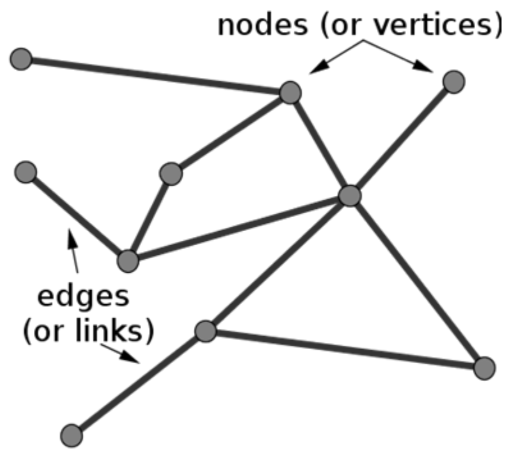


Image from mathinsight.org

(Nykamp 2019)

Figure 4-7 Small network created by vertices and edges

Note: A network can be defined as a graph (nodes and edges have certain attributes). Network theory is also a part of graph theory.

Network theory has been applied in multiple disciplines, including computer science, physics,, operation and communication research. Network analysis methods are applied in urban and regional studies only occurred in the past decade (Sevtsuk and Mekonnen 2012). In the case of the urban street network, edges represent street segments, and nodes represent the junctions where two or more edges interest. Sevtsuk and Mekonnen (2012) mentioned several shortcomings from previous studies: network analysis focused on road segments, a lack of building-level analysis, and unweighted urban network analysis. The authors developed Urban Network Analysis to measure the importance of each node in an urban network setting: reach, gravity index, betweenness, closeness, and straightness. As suggested by Sevtsuk and Mekonnen (2012), this study applied betweenness centrality to identify edges (nodes) with higher centrality in a disaster-affected community.

Betweenness centrality measure node centrality in a graph based on the shortest paths. The betweenness centrality of node v, $C_{btw}(v)$, is measured by the following equation:

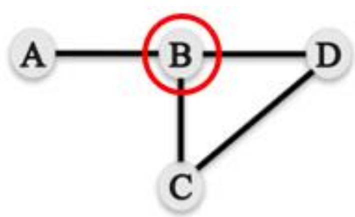
$$C_{btw}(v) = \sum_{s,t} \frac{\sigma_{s,t}(v)}{\sigma_{s,t}}$$

$where$

$\sigma_{s,t} = number\ of\ shortest\ paths\ between\ nodes\ s\ and\ t$

$\sigma_{s,t}(v) = number\ of\ shortest\ paths\ between\ nodes\ s\ and\ t\ that\ pass\ through\ node\ v$

For each pair of nodes in a connected network, there exists at least one shortest path between the nodes such that either the number of edges that the path passes through or the sum of the weights of the edges is minimized. For example, Figure 4-8 illustrates the calculation process of betweenness centrality (node B).



$$C_{btw}(B) = \frac{\sigma_{A,D}(B)}{\sigma_{A,D}} + \frac{\sigma_{A,C}(B)}{\sigma_{A,C}} + \frac{\sigma_{C,D}(B)}{\sigma_{C,D}} = \frac{1}{1} + \frac{1}{1} + \frac{0}{1} = 2$$

Figure 4-8 Betweenness centrality of Node B

With the help of computation power, betweenness centrality can be measured in a complex and large network (see Figure 4-9). The color represents the betweenness centrality of each node (red = min value, and blue = max value).

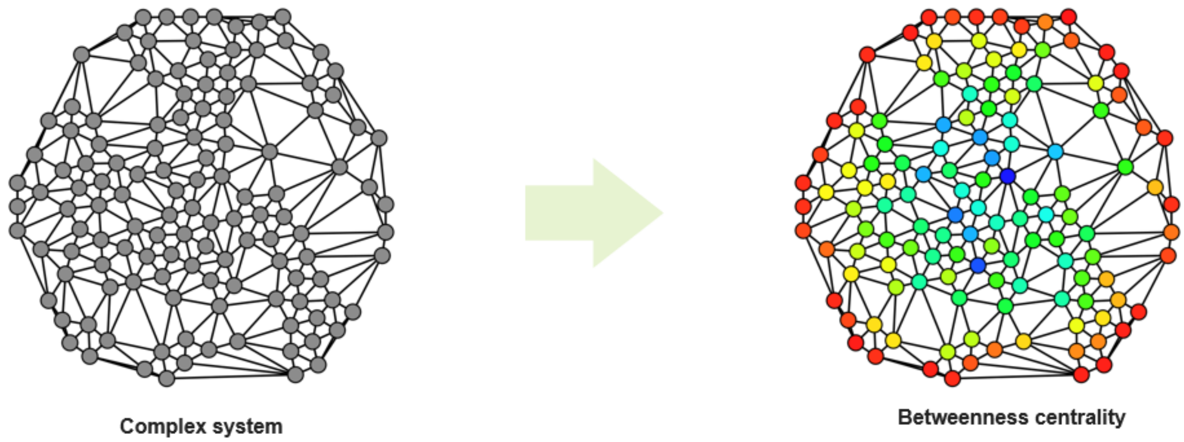


Figure 4-9 Measurement of betweenness centrality in a complex system

Note: Color (from red = min value to blue = max value) represents betweenness centrality of nodes

In an urban network, the generic betweeness centrality is slightly modified to consider building blocks (Sevtsuk and Mekonnen 2012). Betweenness centrality in an urban network, $Betweeness^{r}[i]$, of a building i in graph G estimates the number of times i lies on the shortest path between pairs of other reachable buildings in G that lie within the network raduis r (Freeman 1977).

$$Betweeness^{r}[i] = \sum_{s,t\,\in G-\{i\};d\,[s,t]\leq r} \frac{n_{s,t}[i]}{n_{s,t}} \cdot W[j]$$

$where$

$n_{s,t} = Number\ of\ shortest\ paths\ from\ building\ block\ s\ to\ building\ block\ t\ in\ G$

$n_{s,t}[i]$
$= the\ subset\ of\ these\ paths\ that\ pass\ though\ i, with\ s\ and\ t\ lying\ within\ the\ network\ raduis\ r$
$from\ i$

$W[j] = the\ weight\ of\ a\ particular\ destination\ j$

This study applied a weight, $W[j]$, into particular building blocks and locations that represented critical infrastructure (see Figure 4-10).

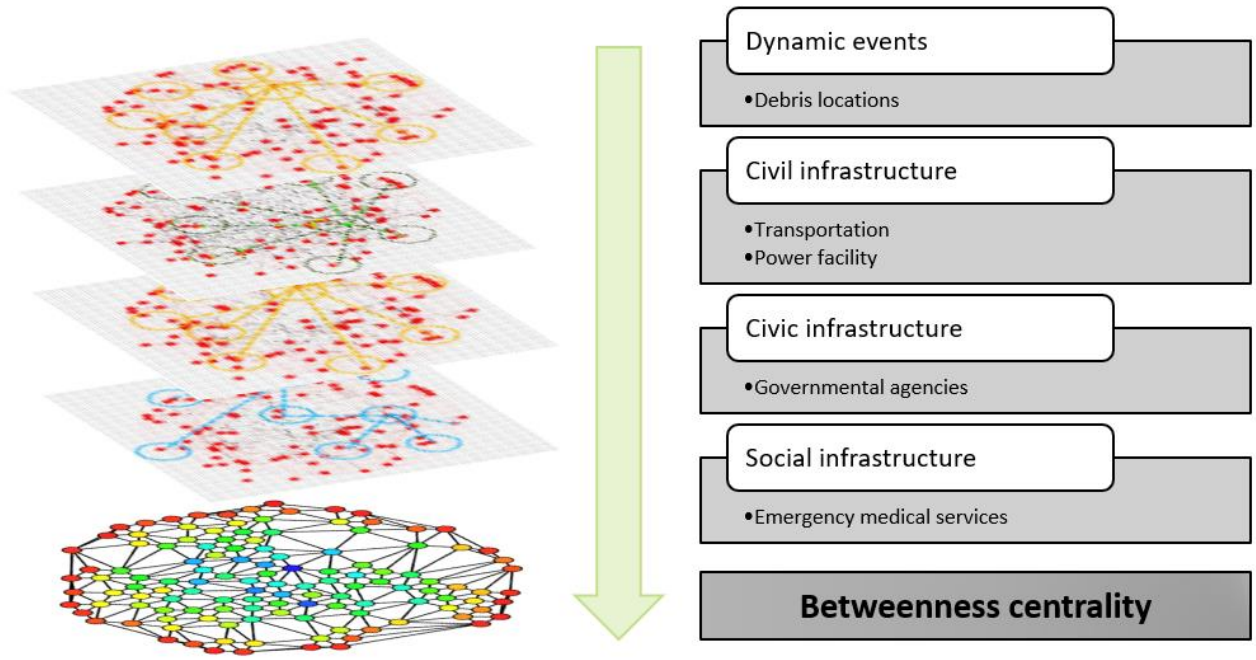


Figure 4-10 Schematic diagram of community structure analysis using network theory and analysis - betweenness centrality

Figure 4-11 demonstrates an example of betweenness centrality results. In this example, each unit (building) has equal weight (1). The color represents the degree of betweenness centrality, with green signifying lower and red signifying higher betweenness centrality.

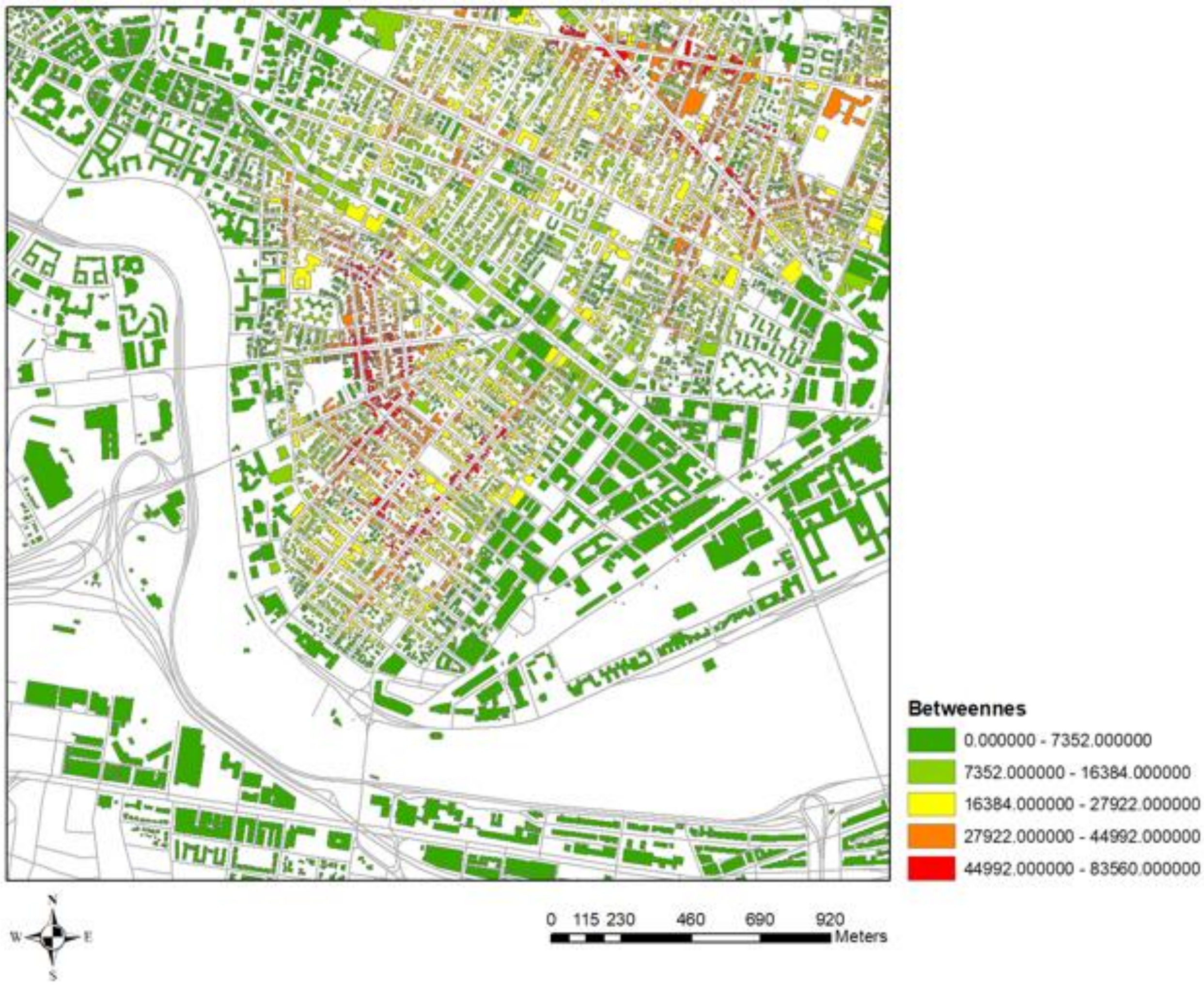


Figure 4-11 Example of betweenness centrality measure

Note: This study used the dataset (Cambridge – Somerville) provided from the Urban Network Analysis toolbox to test betweenness centrality analysis (with equal weight on each building block).

4.2.3 Module#3: TDMS design and selection model

Module#3 is designed to identify an optimal location for TDMSs based on data/information from Modules#1-2. The TDMS design and selection model consists of two steps: land suitability analysis (LSA) and facility location optimization. LSA is a GIS-based process applied to determine the suitability of a specific area for a considered use (i.e., it determines the suitability of an area regarding its intrinsic characteristics) (Cheng and Thompson 2016; Grzeda et al. 2014; Jafari and Zaredar 2010; Leao et al. 2001). After determining suitable locations for installing TDMSs, the optimal location for a TDMS among all suitable locations must be determined. For this determination, facility location problems, location analysis results regarding the optimal placement of facilities (i.e., TDMS in this study) to minimize transportation costs, and multiple other constraints in a given problem set are considered.

Step#1: Land suitability analysis

Land suitability for a TDMS is measured by three performance quantifiable parameters: technical, environmental, and social performance. This study employed a hybrid mathematical method integrating fuzzy and Boolean logic. Figure 4-12 describes the overall LSA process and the three performance score systems using fuzzy and Boolean logic.

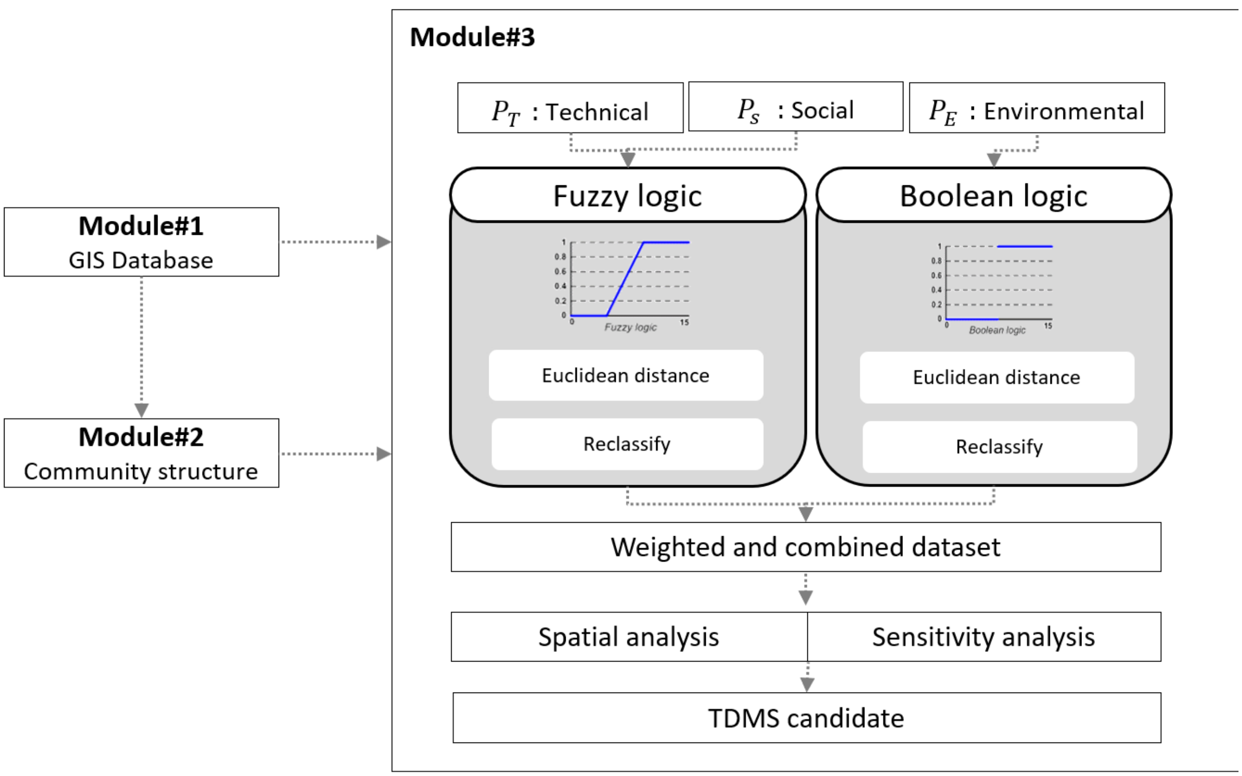


Figure 4-12 Model structure in Module#3

Performance score measurement

As further discussed in Chapter 3, this study defines three quantifiable performance parameters: technical, environmental, and social performance. Technical performance (P_T) measures engineering performance due to spatial characteristics; environmental performance (P_E) measures the existing and emergent regulatory performance of different zones based on EPA guidelines; and social performance (P_S) measures the social impact (e.g., noise, odor, and traffic) on residential areas from certain TDMS locations. Figure 4-13 is a schematic diagram of three performance measurements in spatial dimensions.

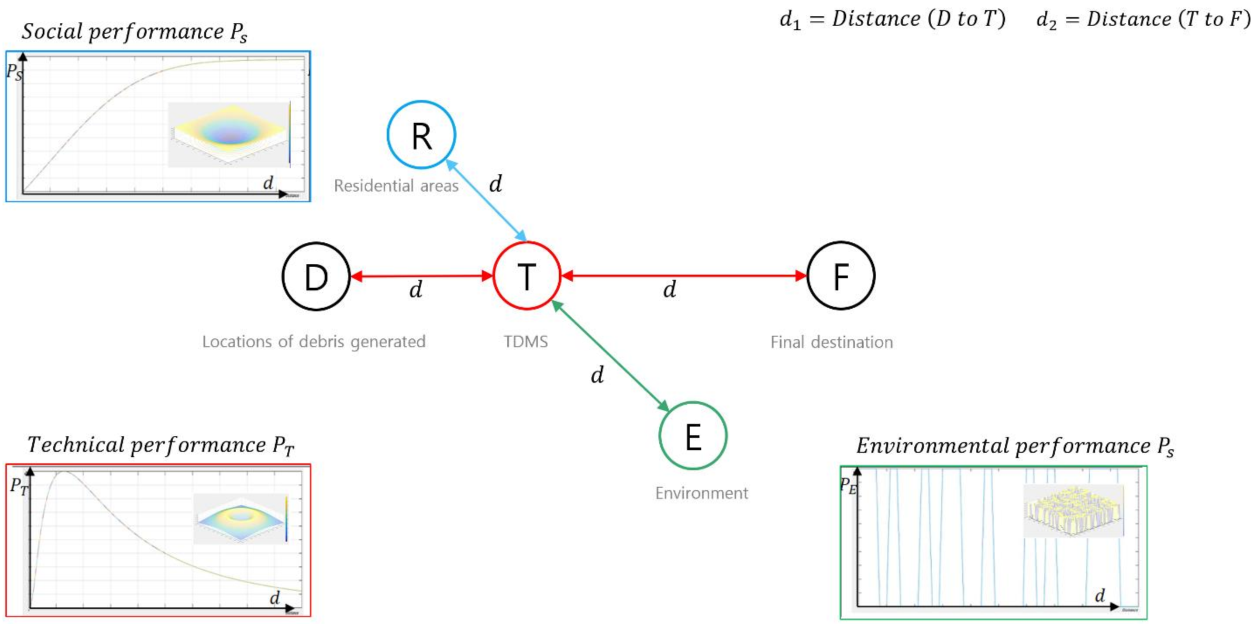


Figure 4-13 Measuring performance for siting TDMSs

Note: Social performance increases when a TDMS is located far from residential areas, and technical performance varies by the locations of debris and final destinations. Environmental performance is determined by nature and built environment in a community.

To determine the three performance scores, this study employed Fuzzy and Boolean logic: Fuzzy logic is an approach to compute based on "*degrees of truth*" compared to "*true or false approach"* (i.e., Boolean logic) (Duch 2005). Fuzzy logic can be represented by a sigmoid function (see Figure 4-14).

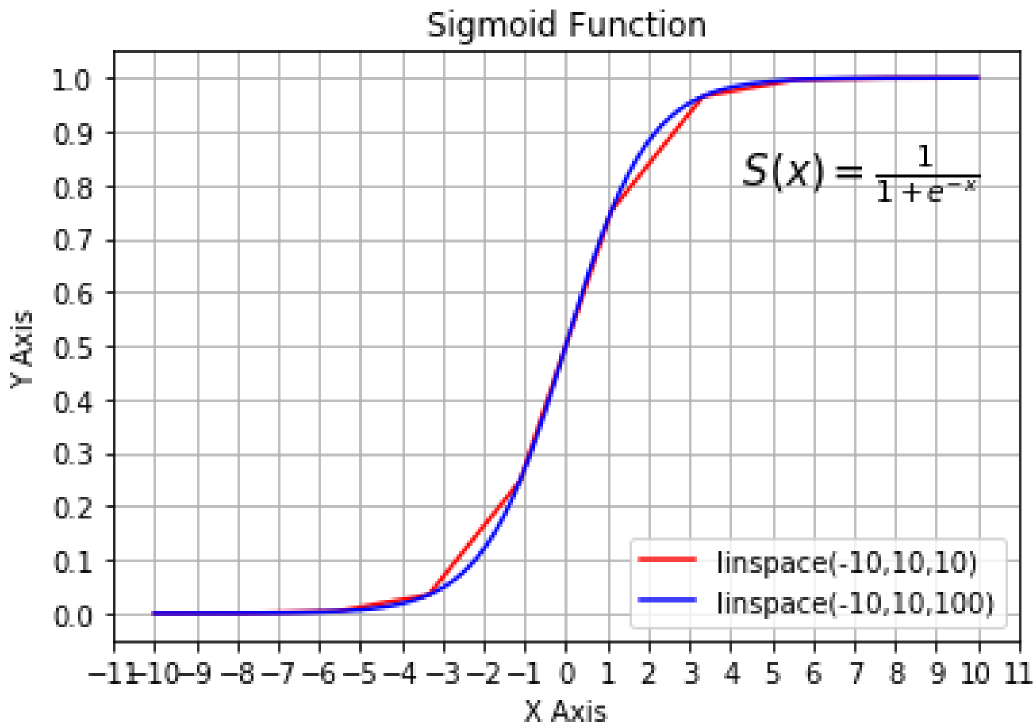
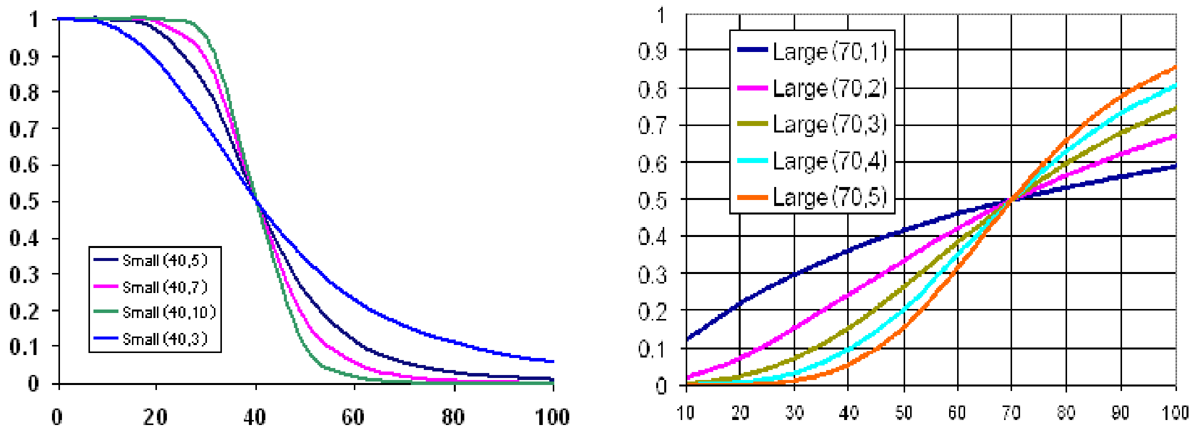


Figure 4-14 Sigmoid function graph

Note: Sigmoid function is a mathematical function with the characteristic of an "S"-shaped curve or sigmoid curve.

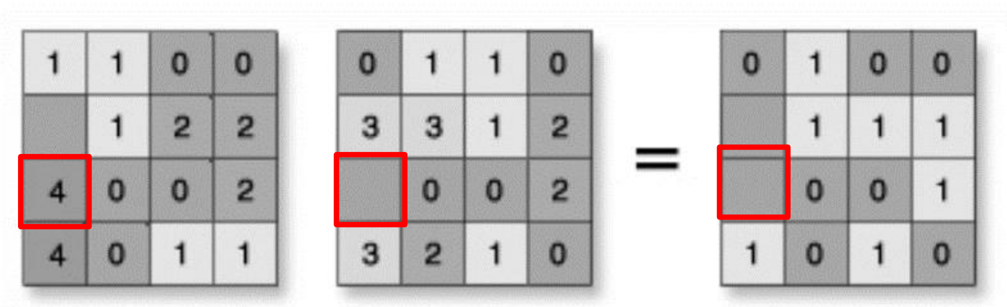
In spatial analysis, there are seven types of fuzzy membership functions: gaussian, large, linear, MS large, MS small, near, and small. In this study, Fuzzy small and MS large functions were used. The Fuzzy small function is used when smaller input values are more likely to be a member of the set and the Fuzzy large function is applied when larger input values are more likely to be a member of the set (see Figure 4-15).



(a) Fuzzy Small transformation function (b) Fuzzy MS Large transformation function

Figure 4-15 Fuzzy small and MS large transformation functions for reclassifying/transforming the input data to a 0 to 1 scale

Boolean logic is a form of algebra centered on three simple words, called Boolean operators: *OR*, *AND*, and *NOT*. Thus, all values are either true or false. Figure 4-16describes how Boolean logic is processed with the operator *AND*.



Input rater data#1 *"AND"* input raster data#2 = output raster

Figure 4-16 Illustration of Boolean logic

Note: When a cell in raster data does not have a value, the output will be NULL: Input raster value on raster data#1 and 2 is 4 and null. So, the output value becomes 0.

This study applied Fuzzy and Boolean logics to calculate performance scores (see Table 4-3), for example, for road accessibility and residential areas.

Table 4-3 Logic criteria

Logic		Criteria*	Value* 0	Value* 1	References
Boolean	C1	100-year floodplain			EPA (1995)
Boolean	C2	Surface water/water stream	Buffer 3280 feet (1km)		LDEQ (2017)
Boolean	C3	Wetlands/swamp	<=100 feet		LDEQ (2017)
Boolean	C4	Distance from protected/historical area	<=1640 feet		Chen and Thompson (2016)
Boolean	C5	Land slope	Slope > 10%	Slope <=10%	Chen and Thompson (2016)
Boolean	C6	Distance from businesses, schools, hospitals, clinics (for chipping and grinding)	<= 300 feet		LDEQ (2017)
Boolean	C7	Distance from businesses, schools, hospitals, clinics (for burning debris)	<= 1000 feet		LDEQ (2017)
Boolean	C8	Airport	<=10,000 feet		LDEQ (2017)
Fuzzy	C9	Road accessibility	<=1640 feet (500m)		Chen and Thompson (2016)
Fuzzy	C10	Residential area (noise and odor)	328 – 3280 feet (0.1km – 1km)		Christensen, Manfredi and Kjeldsen (2011)

** Criteria were designed based on guidelines from the U.S. EPA and LDEQ. When certain values for a criterion were not provided (e.g., they were left up to the preference of decision makers), values were retrieved from the other studies on the reference column on the right side.*

For example, Boolean logic is applied to C1, which is the 100-year floodplain. This means for any cell in raster data within a 100-year floodplain, 0 is given to that cell. The Fuzzy small transformation function is applied (midpoint = 500m, spread = 5) in C9.

To integrate the performance scores of each cell, the following performance scoring equation was developed: Table 4-4 describes the detail parameter inputs for each performance score.

$$\boldsymbol{P} = \left[\boldsymbol{\alpha P_T} + (1 - \boldsymbol{\alpha})\boldsymbol{P_s}\right] * \boldsymbol{P_E}$$

Table 4-4 Parameters in the performance scoring method

Parameter	Description
P	Total performance score
$P_T = P_T\ (T_R\ , T_{TDMS}, T_F\ , \ldots)$	Technical performance score
T_R	Resource capacity (e.g., number/type of resources)
T_{TDMS}	TDMS capacity (e.g., number/location of TDMS)
T_F	Capacity of final destinations (e.g., location, distance, capacity)
$P_S\ = P_S\ (S_N\ , S_D\ , \ldots)$	Social performance score
S_P	Perception of need (affected or non-affected)
S_D	Distance from residential areas to a TDMS
$S_{\mathbf{s}}$	Social influence
P_E	Environmental regulation indicator $P_E\ = 0\ : restricted\ ,\ P_E\ = 1 : unrestricted$
α	Decision makers' preference depending on disaster severity and community needs ($0 \leq \alpha \leq 1$)

Note: Decision makers' parameter, α, is applied to give more or less weight to either technical or social performance based on decision makers' preference or circumstances after a catastrophic event.

For instance, calculated performance scores are stored in a raster format (see Figure 4-17). Then, the values of P_T , P_S , $and\ P_E$ are integrated into P

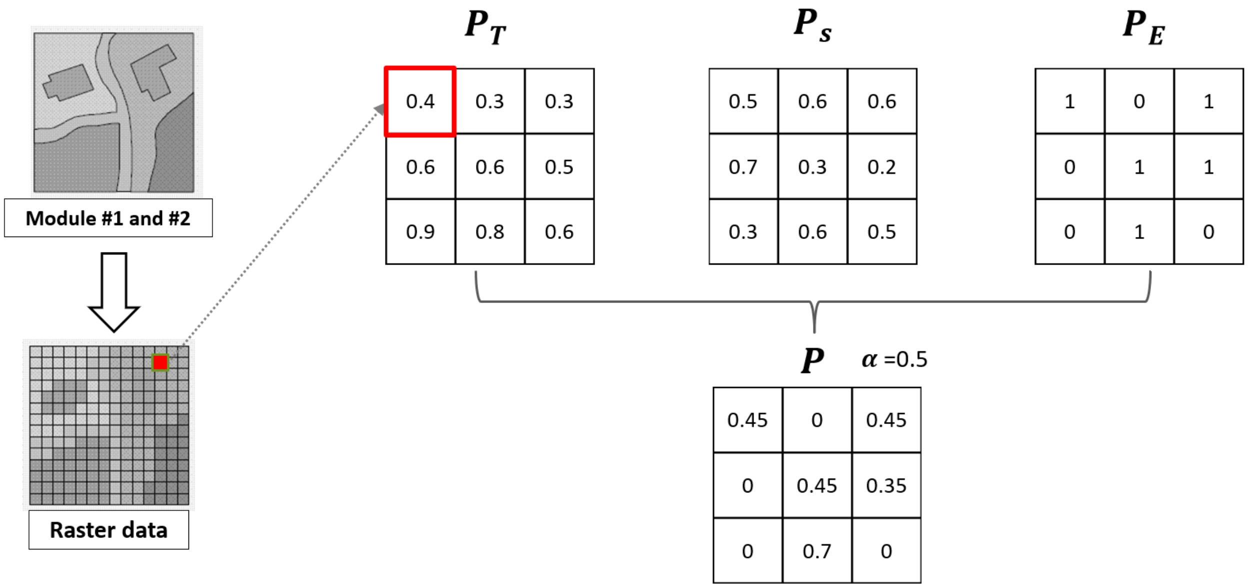


Figure 4-17 Schematic diagram of the performance scoring method

Note: The cell size (spatial resolution) used in this study was 625 m^2 *(25 x 25 m) as this is small enough to capture TDMS locations but large enough to perform computational analysis efficiently* (Esri 2008).

Finally, this study developed a python toolbox using ArcGIS ModelBuilder (version. 10.5) to automate the entire process of Step#1 (land suitability analysis). In general, a model in ModelBuilder consists of at least three elements: input data (blue square), geoprocessing tools (yellow circle), and output data (green square). Figure 4-18 demonstrates a small part of the entire geoprocessing model in Figure 4-22.

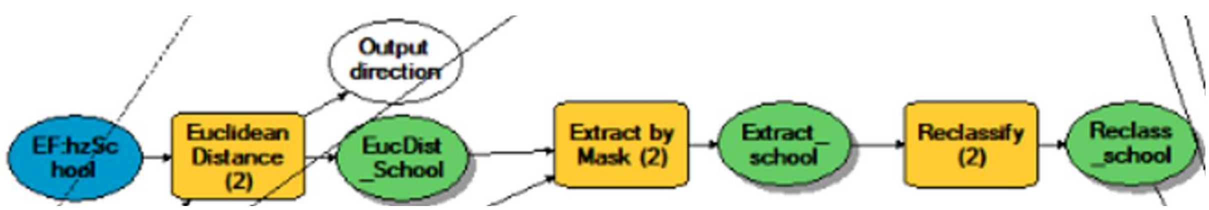


Figure 4-18 Model developed by ArcGIS ModelBuilder for land suitability analysis

Note: the entire LSA model is described in Figure 4-22.

Based on the school dataset (blue circle - EF:hz School), Euclidean distance is calculated using the equation in Figure 4-19.

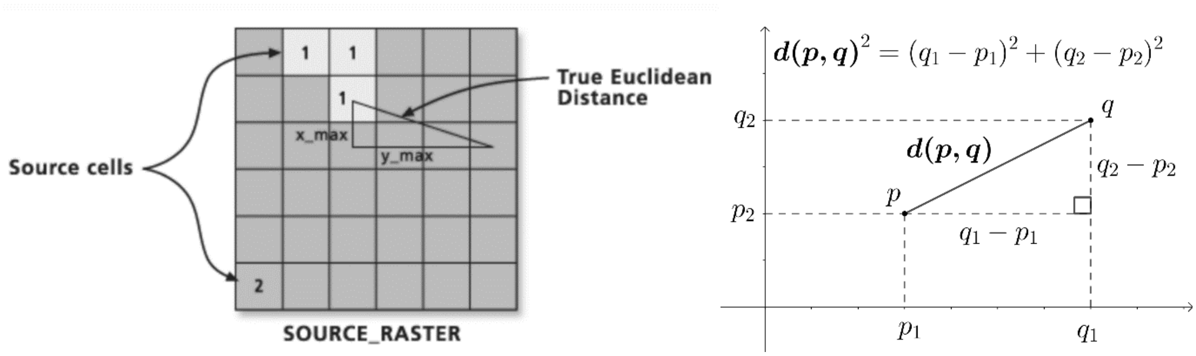
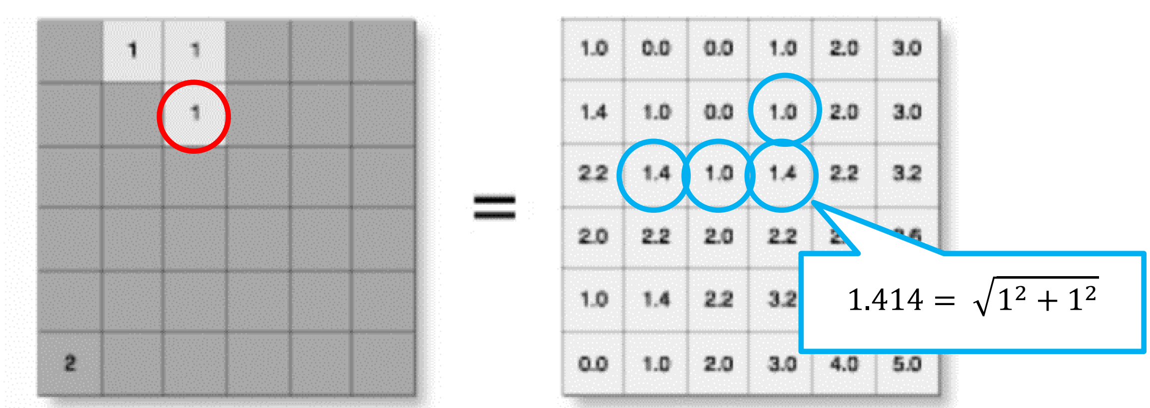


Figure 4-19 How to measure Euclidean distance in a raster data format

Image from By Kmhkmh, https://commons.wikimedia.org/w/index.php?curid=67617313
Note: Euclidean distance is calculated from the center of the source cell (where schools are located) to the center of each of the surrounding cells.

Figure 4-20 demonstrates how Euclidean distance is measured based on the source raster. The Euclidean distance is calculated to the closest source. For instance, the values on the blue circles on the right side are calculated based on the distance from the red-colored raster source data:

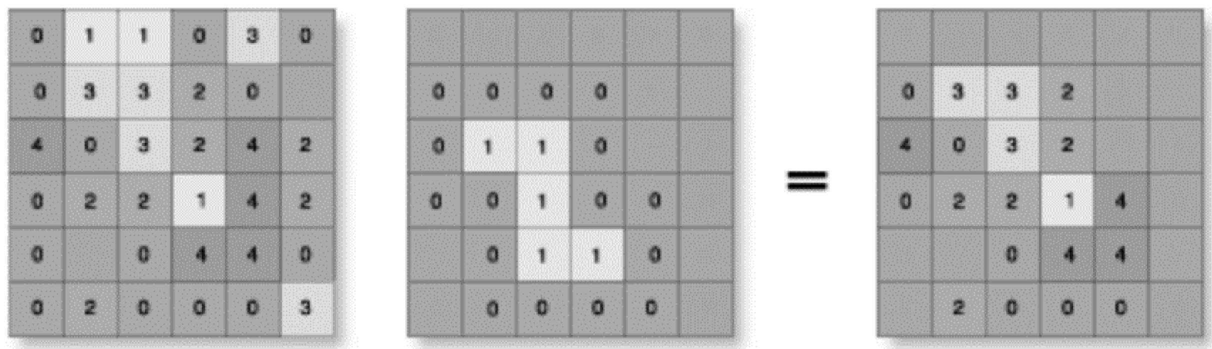


Source_raster **Euc_Distance**

Figure 4-20 Measuring Euclidean distance from certain raster

Note: Syntax in python: EucDistance (in_source_data, {maximum_distance}, {cell_size}, {out_direction_raster}). The image was downloaded from Esri ArcGIS

Output data (EucDist_School) is used as input data for the *Extract by Mask* function. This function extracts the cells of a raster that corresponds to the area defined by a mask (EucDist_School).



InRas InMas OutRas

Figure 4-21 Illustration of *Extract by Mask function*

Note: OutRas contains only the values in InRas under the raster with certain values in InMas. The image was downloaded from Esri ArcGIS

The output data (Extract_School) is processed by the *Reclassify* function to reclassify the values in a raster from 0 to 1.

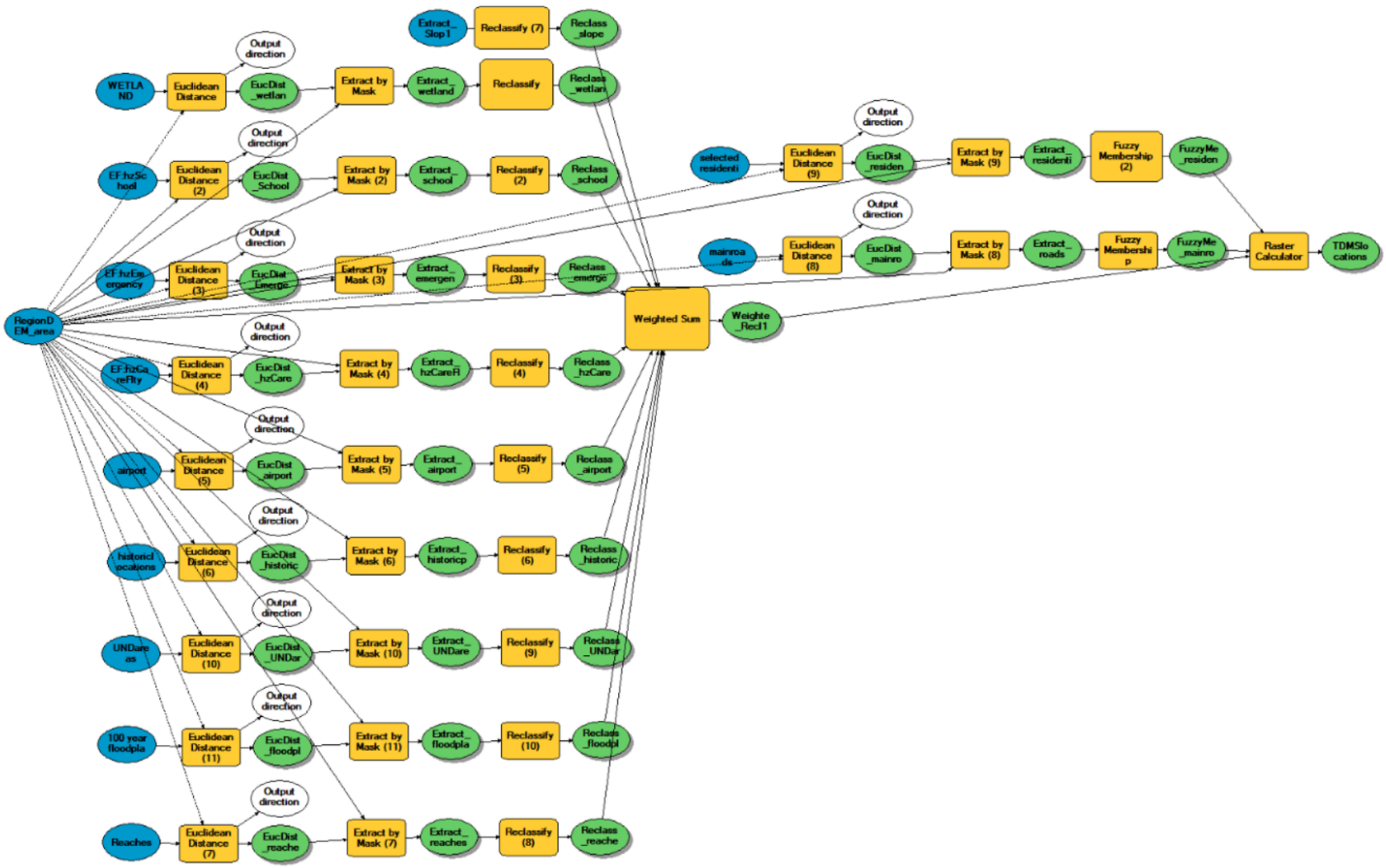


Figure 4-22 Python toolbox to automate the entire process of land suitability analysis

Note: The detail codes in the python toolbox are described in Appendix#A.

Step#2: Optimal location of TDMS

Most of funding for debris removal are spent for transporting debris (U.S. Department of Homeland Security 2011). Thus, it is critical to locate TDMSs to minimize the cycle time of debris-hauling trucks: Peurifoy et al. (2010) defined the cycle time required by a truck for transport of materials in divided into the following four elements: *load, haul, dump* and *return time*. Searching for the optimal location of a TDMS is considered a p-median problem (Daskin and Maass 2015; Kim et al. 2018b). A p-median problem is a specific type of a discrete location model designed to place p facilities to minimize the (demand-weighted) average distance between a demand node and the location in which a facility was placed. This serves as an approximation of total delivery cost. In this model, there are no capacity constraints of the facility.

Mathematical model: This study formulates the problem set using an undirected (bi-directional) graph $G = (I, J, E)$, where the demand nodes (i.e., locations of debris) are represented by a set of vertices $i \in I$, the available locations of TDMSs (determined by land suitability analysis) are represented by another set of vertices $j \in J$, and edges (road network) $e_{i,j} \in E$ only exist between vertices from $i \in I$ to those in $j \in J$ (note: the road network set, E, could be updated/revised based on the condition of the road network before/after a disaster). Further, positive weights are given to the edges, $d_{i,j} \geq 0$, which represents the distance (measured by the road network dataset in Module#1) between vertices i and j (note: it is possible to have zero distance between a demand node i and a possible facility location j). Finally, positive weights are given to the demand nodes (i.e., the amount of debris in a pickup location) h_i for $i \in I$. In this problem set, the objective of this mathematical model is to place p number of TDMSs to minimize the total distances between a demand node i (debris pickup location) and its assigned TDMS j.

Integer linear programming (ILP) was applied to solve the problem set above. This study defined a decision variable, Y_{ij}, which signifies which demand node, i, are serviced by which facility location, j.

$p \quad = Number\ of\ TDMS\ to\ locate$

$$Y_{i,j} = \begin{cases} 1\ if\ debris\ pickup\ location\ i \in I\ assigned\ to\ facility\ located\ at\ j \in J \\ 0, otherwise \end{cases}$$

Another decision variable is defined below

$$X_j = \begin{cases} 1,\ \ if\ TDMS\ facilty\ located\ at\ j \in J \\ 0, otherwise \end{cases}$$

Given the two decision variables, this study can formulate the p-median problem as the following ILP:

$h_i\ \ = amount\ of\ debris\ at\ location\ at\ i$

$d_{i,j} = distance\ from\ debris\ pickup\ location\ at\ i\ to\ TDMS\ location\ at\ j$

$$min \sum_{i \in I} \sum_{j \in J} h_i\ \ d_{ij} Y_{ij}$$

$s.t.$

$$\sum_{j \in J} Y_{ij}\ = 1, \qquad \forall i\ \in I$$

$$Y_{ij}\ - X_j\ \ \leq 0, \forall i\ \in I, j \in J$$

$$\sum_{j \in J} X_j\ \ = p$$

$$X_{ij}\ \in \{0,\ 1\} \qquad\qquad \forall j \in J$$

$$Y_{ij}\ \in \{0,\ 1\},, \forall i\ \in I\ , j\ \in J$$

The objective function, $min \sum_{i \in I} \sum_{j \in J} h_i\ \ d_{ij} Y_{ij}$, minimizes the demand-weighted (i.e., weighted by h_i) distance $d_{ij} Y_{ij}$ summed over all facilities and demand notes. The first constraint, $\sum_{j \in J} Y_{ij}\ = 1$, implies that a demand node i can be serviced by one facility. The second constraint,

$Y_{ij} - X_j \leq 0$, indicates that demand node i can be serviced by a facility at j, only if there is a facility at j, because if $X_j = 0$ then it must be that $Y_{i,j} = 0$. The third constraint, $\sum_{j \in J} X_j = p$, indicates that p facilities should be located. Lastly, $X_{ij} \in \{0, 1\}, Y_{ij} \in \{0, 1\}$ forces the decision variables to be binary.

The mathematical model is, then, solved by a heuristic algorithm plugged in ArcGIS's ArcMap (version 10.5). The process is described below (Esri 2019):

1. Location-allocation solver generates an origin-destination matrix of shortest-path costs between all the facilities and demand point locations along with the network.
2. It then constructs an edited version of the cost matrix by a process known as Hillsman editing (Hillsman 1980). It enables the same overall solver heuristic to solve numerous problem types.
3. Location-allocation solver produces a set of semi-randomized solutions and applies a vertex substitution heuristic (Teitz and Bart 1968) to refine these solutions, creating a group of good solutions.
4. Meta-heuristic combines this group of good solutions to create better solutions. When additional improvement is impossible, the metaheuristic returns the best solution. The combination of an edited matrix, semi-randomized initial solutions, a vertex substitution heuristic, and a refining metaheuristic quickly yields near-optimal results.

This study applied the model above into a small-scale network below to illustrate the general process.

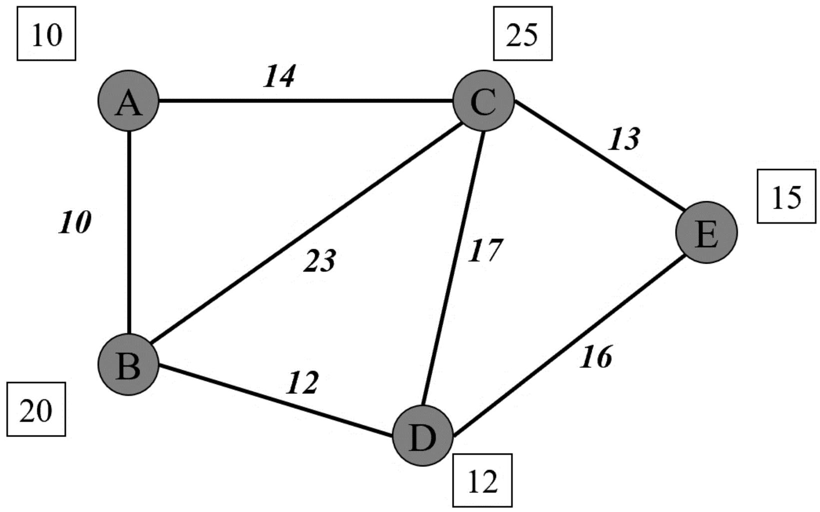


Figure 4-23 Description of a network example

Note: Number in a box refers to the amount of debris unit at a specific node, and a number on line refers to distance.

The formulation for the given network dataset is below.

$Minimize\ \ 10(0)Y_{AA} + \ 20(10)Y_{BA}$ + 25(14) Y_{CA} + … + 15(0) Y_{EE}

Subject to;

$Y_{AA} \leq X_A$

$Y_{BA} \leq X_A$

…

$Y_{EE} \leq X_E$

$X_A + X_B + X_C + \ X_D + \ X_E$ = p (p =1 in this example)

$Y_{AA} + Y_{AB} + \cdots + Y_{AE} = 1$

…

$Y_{EA} + Y_{EB} + \cdots + Y_{EE} = 1$

$X_A, X_{B,}, \ldots, X_E \in \{0,\ 1\}$

$Y_{AA}, Y_{BA}, \ldots, Y_{EE} \in \{0,\ 1\}$

Then, facility C (14*10 + 23*20 + 17*12 + 13*15 = 999) is selected as the optimal location under the network dataset above. .

This study involved a hypothetical scenario in which there are 10 available facilities where TDMSs can be installed for debris removal operation and 26,513 debris pickup locations in a disaster-affected community. The proposed optimization model was applied to determine an optimal TDMS location.

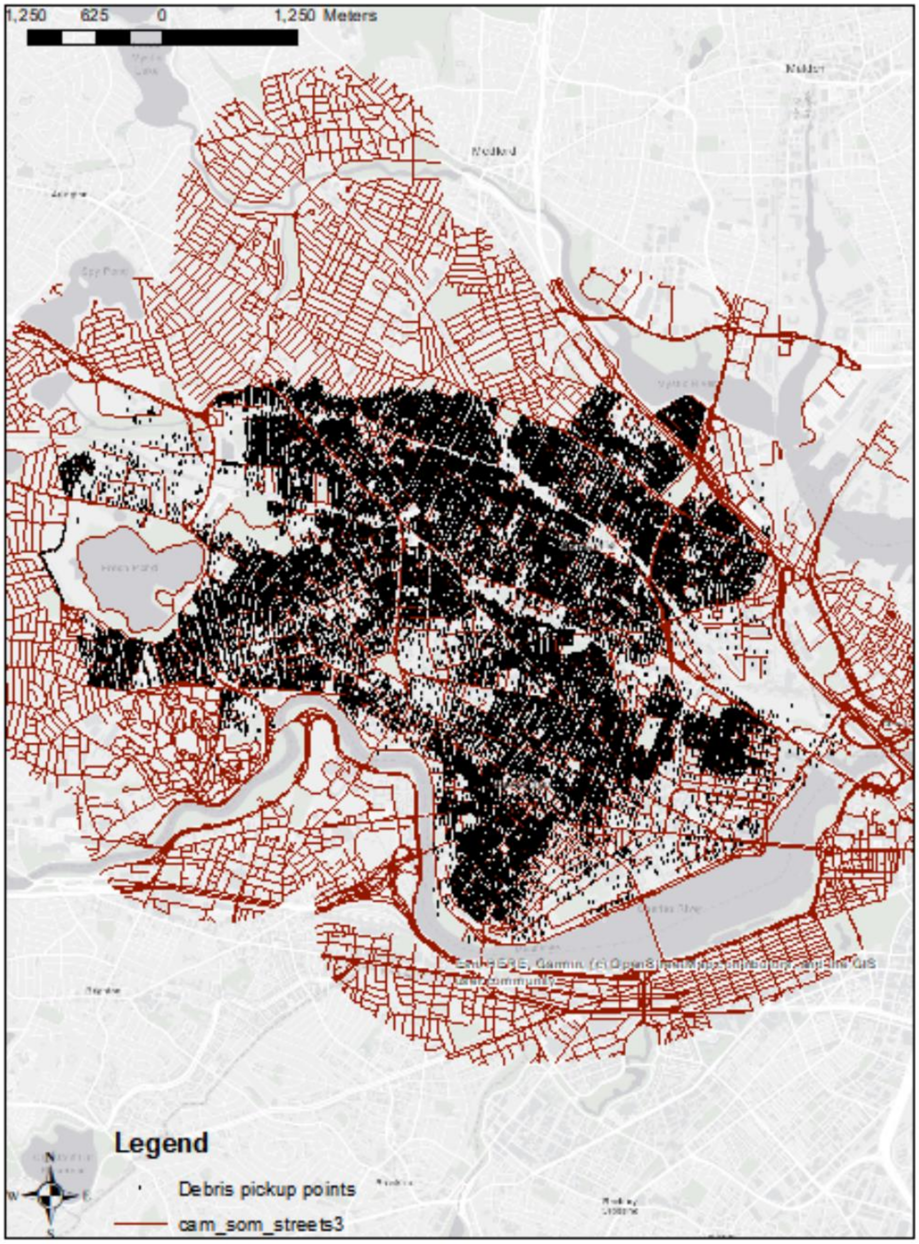


Figure 4-24 Debris pickup locations and road network

Note: Black dots represent 26,513 debris pickup locations, and red lines represent the road network in a city. There were no road blockages in this scenario.

The location-allocation solver generated an origin-destination matrix of shortest-path costs (i.e., total length in this scenario) between all the facilities (DestinationID) and demand point (OriginID) locations along with the network. The total number of generated records in the OD matrix was 265,130 (equal to 26,513 (debris pickup points) * 10(TDMS facility locations)).

OriginID	DestinationID	DestinationRank	Total_Length
1	5	1	268.899503
1	1	2	1858.031715
1	9	3	2799.768235
1	2	4	3043.921993
1	8	5	3884.068545
1	4	6	4489.533028
1	3	7	4689.671347
1	6	8	4761.985769
1	7	9	5158.313279
1	10	10	6021.319463
2	5	1	225.344403
2	1	2	1814.476615
2	9	3	2756.213135
2	2	4	3000.366893
2	8	5	3840.513445
2	4	6	4445.977928
2	3	7	4646.116247
2	6	8	4718.430669
2	7	9	5114.758178
2	10	10	5977.764362
3	5	1	173.66878
3	1	2	1818.802643
3	9	3	2760.539163
3	2	4	3004.692921

Figure 4-25 Snapshot of OD matrix created

Note: OrigineID refers to debris pickup locations, DestinationID refers to possible TDMS locations, and DestinationRank refers to a rank (based on Total_Length) within a set of OriginID.

Figure 4-26 to 4-27 describes the selected facilities (marked with a red-colored star) for each scenario.

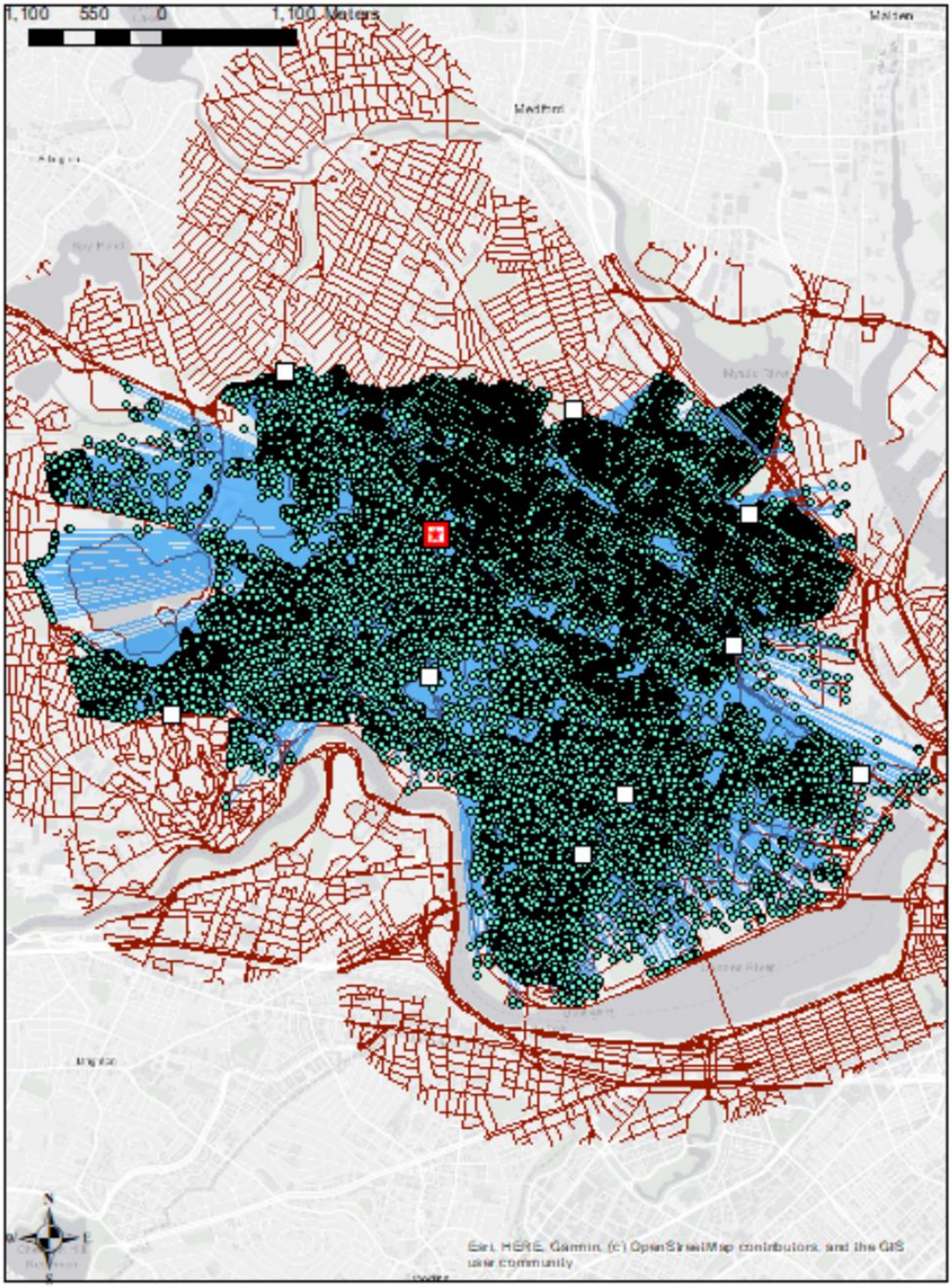


Figure 4-26 Selected facility when only one TDMS is required

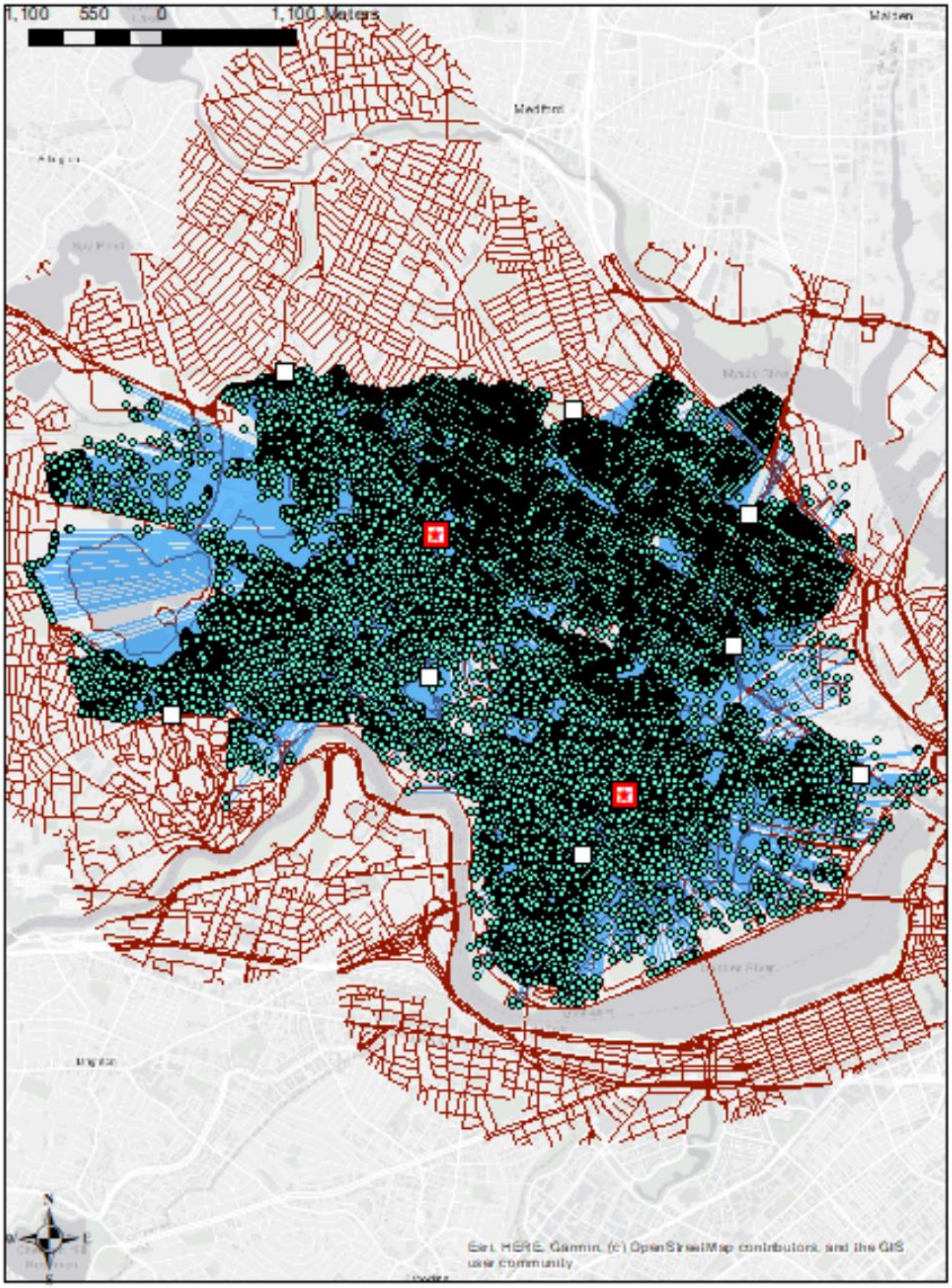


Figure 4-27 Selected facilities when two TDMSs are required

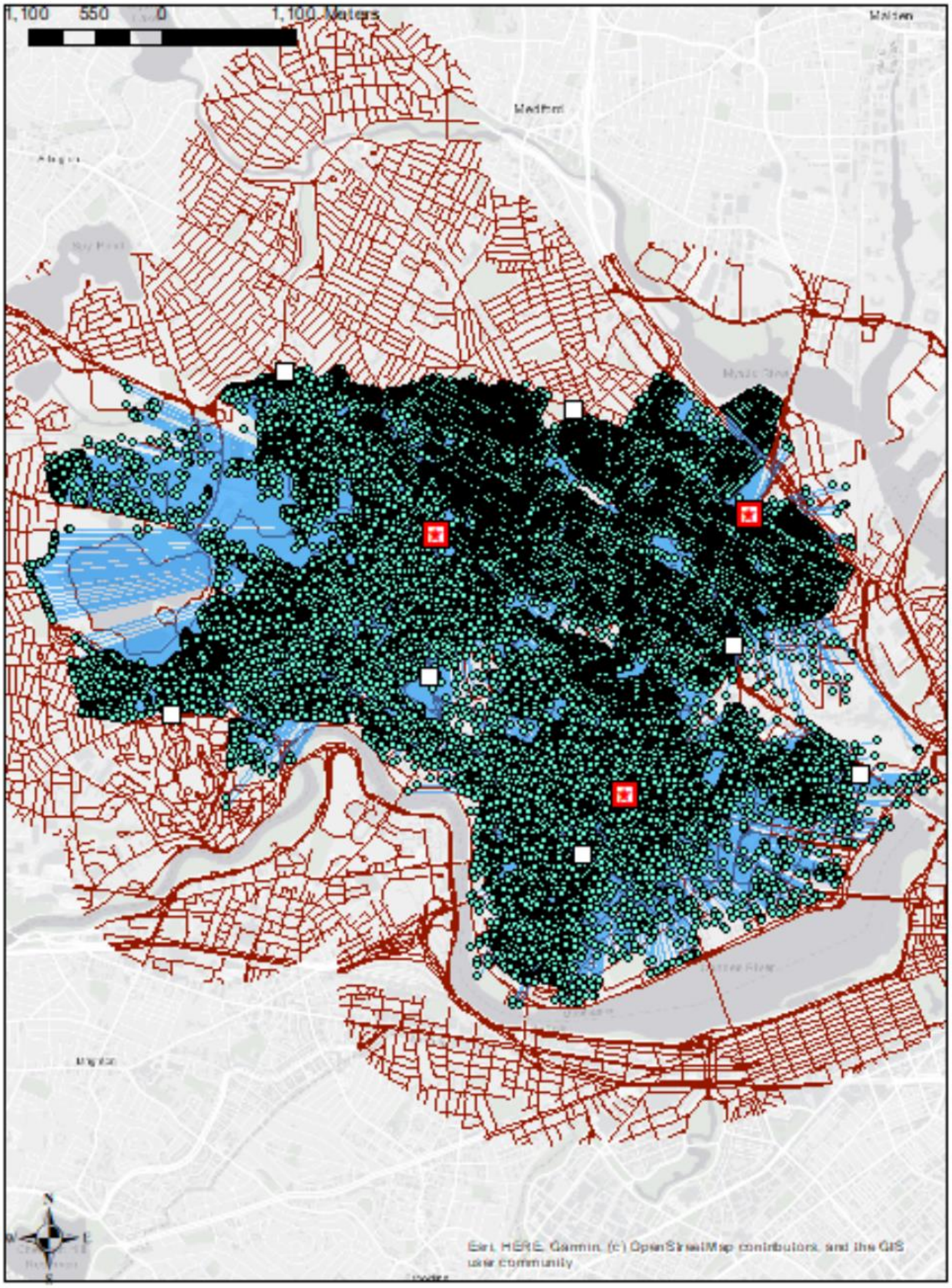


Figure 4-28 Selected facilities when three TDMSs are required

4.2.4 Module#4 Agent-based modeling

To simulate complex post-disaster debris management systems under multiple post-disaster scenarios, this study employed agent-based modeling. Compared to system dynamics and discrete events, ABM has several advantages when simulating complex systems (i.e., debris management system). These advantages include: (i) ABM captures emergent phenomena generated by either a disaster or interactions between agents; (ii) ABM provides a natural description of a system (bottom-up approach); and (iii) ABM is flexible to deal with emergent dynamics in complex systems (see Figure 4-29) (Cimellaro et al. 2017; Macal and North 2008; Sumari and Ibrahim 2013; Turrell 2016; Zheng et al. 2013).

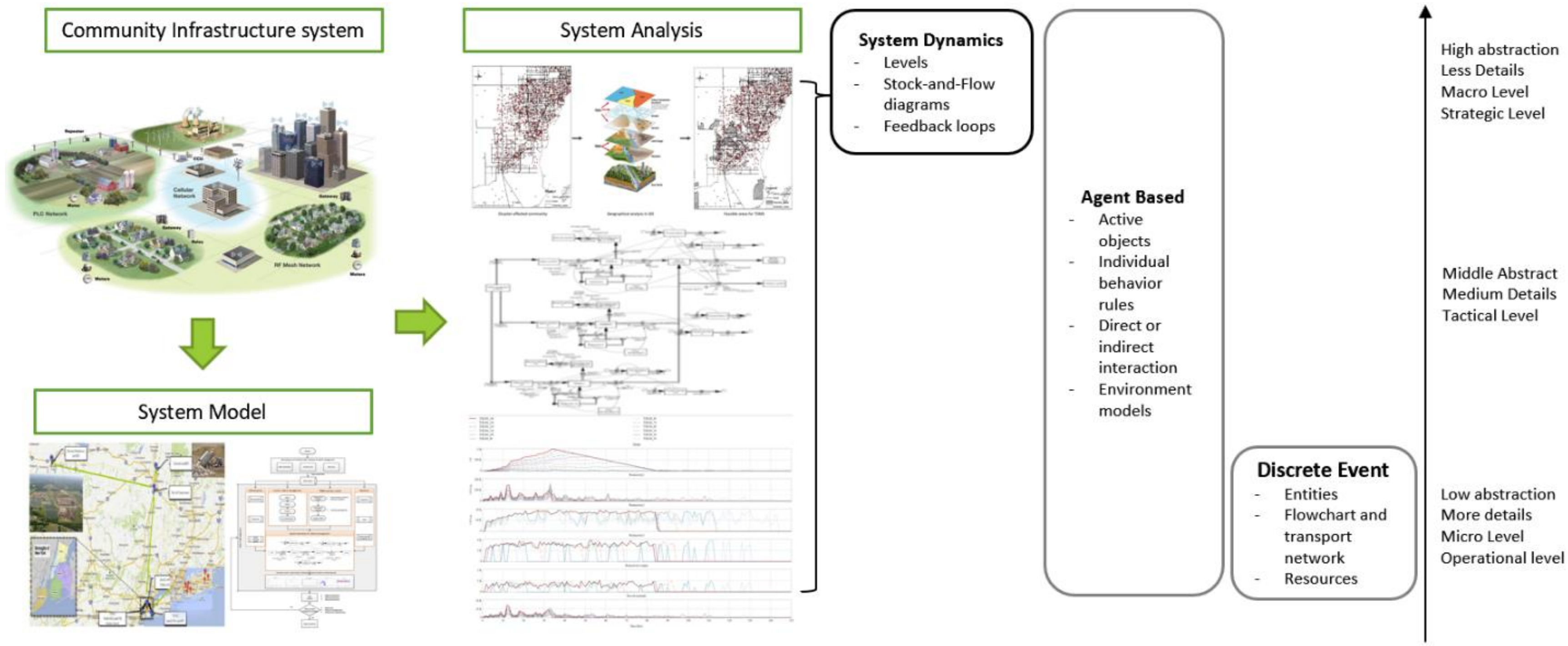


Figure 4-29 Comparison of simulation methods: DE, SD and ABM

ABM consists of three basic elements: agent, environment, and rules (see Figure 4-30). The following outlines the detailed design process of the three elements to simulate debris management systems.

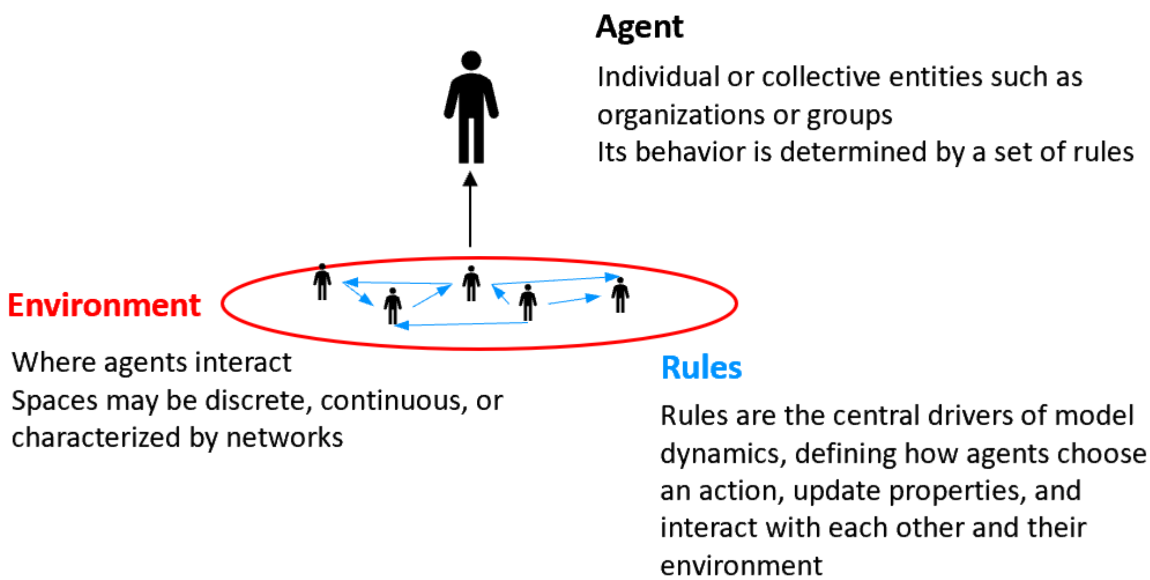


Figure 4-30 Three basic elements of ABM

Four types of agents were created: *debris*, *TDMS*, *truck*, and *landfill* (see Figure 4-31). The *debris* agent is created immediately after a disaster event, and locations and amounts of debris are the main parameters. This agent is estimated based on the Federal Emergency Management Agency (FEMA)'s Hazus-MH debris estimation tool (ver. 4.2. Service Pack 3.0). The *truck* agent represents any vehicles transporting debris generated from the disaster to a designated location. The *truck* agent contains two parameters: vehicle speed and capacity. The average speed of truck is 45 miles/hour, and there are two truck capacities, namely 25 and 50 cubic yards. The *TDMS* agent includes multiple debris processes (represented as discrete events) such as chipping, burning, sorting, and storing debris. The *landfill* agent represents the destination of debris transported from *TDMS* (e.g., landfills and recycling companies). Hourly processing time is a parameter is created in the agent.

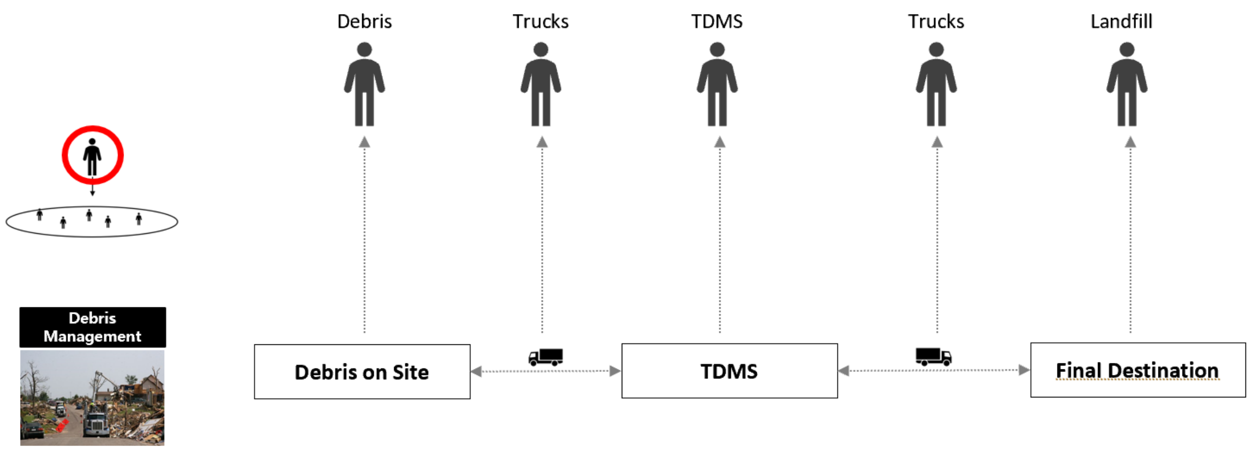


Figure 4-31 Types of agents created in adaptive DSS

Figure 4-32 describes the fundamental structure of ABM. As outlined above, ABM consists of agents, environments, and rules. In this study, the environment is designed using the GIS platform that is created by Modules#1-2. It includes the transportation network, facility locations, and debris locations. The decision space includes rules of agent behavior as well as multiple parameters of agents. Finally, agents represent debris, trucks, TDMS, and landfill.

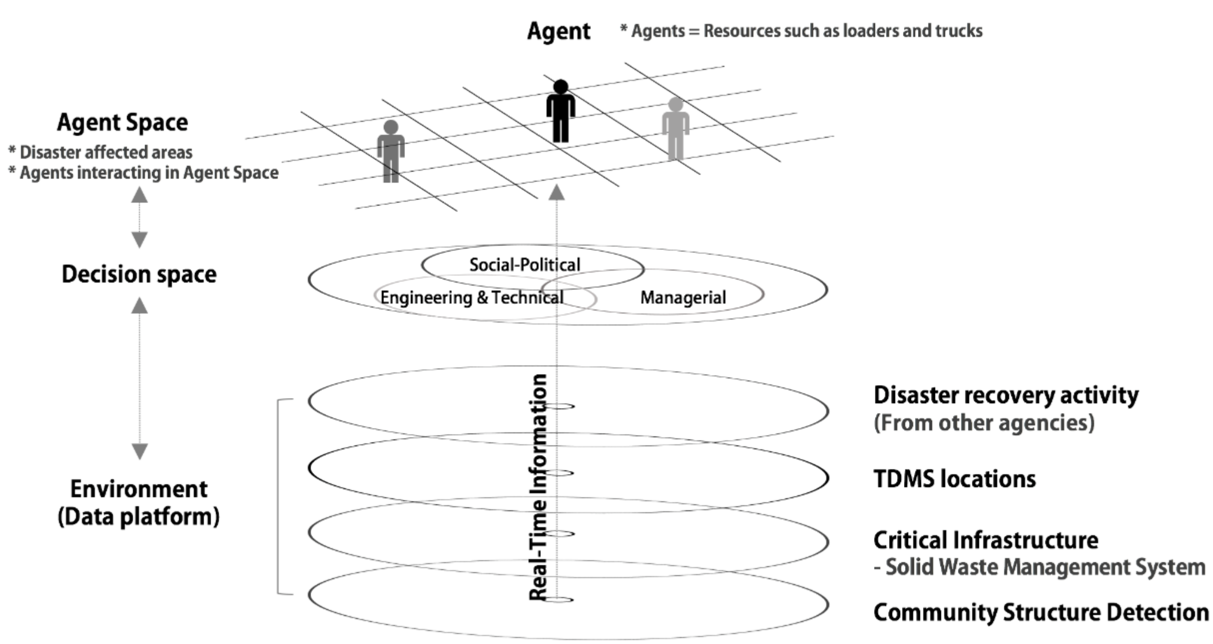


Figure 4-32 Elements of ABM in the adaptive decision support system

In recent years, the ABM community has developed multiple ABM toolkits that enable individuals to develop ABM applications, such as Netlogo, RePast, AnyLogic, and Mesa. This study developed a tool to simulate, analyze, and visualize an ABM model with the help of AnyLogic simulation software. Table 4-5 describes the basic icons and functions applied in the ABM model.

Table 4-5 AnyLogic icon descriptions

Icon	**Type**	**Descriptions**
	Source	*Generates agents*
	Sink	*Disposes of incoming agents*
	Delay	*Delays agents by the specified delay time*
	Queue	*Stores agents in the specified order*
	Hold	*Blocks/unblocks the agent flow*
	MoveTo	*Moves an agent from its current location to a new location*
	ResourcePool	*Provides resources seized and released by agents*
	Seize	*Seizes the certain number of units/agents*
	Release	*Releases resources previously seized by agent*
	Service	*Seizes resource units for the agent, delays them, and releases seized units*
	ResourceTaskStart	*Defines the start of the flowchart branch modeling the task process for resource units*
	Resource TaskEnd	*End point of flowchart*
	ResourceTask	*Tasks for certain resources that can not be designed by functions provided such as failures, maintenance, and breaks*
	Enter	*Inserts agents created elsewhere into the flowchart*
	Exit	*Accepts agents coming to*
	Batch	*Accumulates agents, then outputs them into a new agent*
	Unbatch	*Extracts all agents*

Note: Detailed descriptions are in Appendix#C

A event of disaster creates an agent, *debris* (see Figure 4-33). There is a *delay* function to consider the debris handling time from home to curbside. This study assumed that residents evacuated before/during a disaster and returned to the community within 40 days of the disaster event (this part was modeled by system dynamics). A ratio of *evaluated* and *backtocommunity* was applied in the delay function.

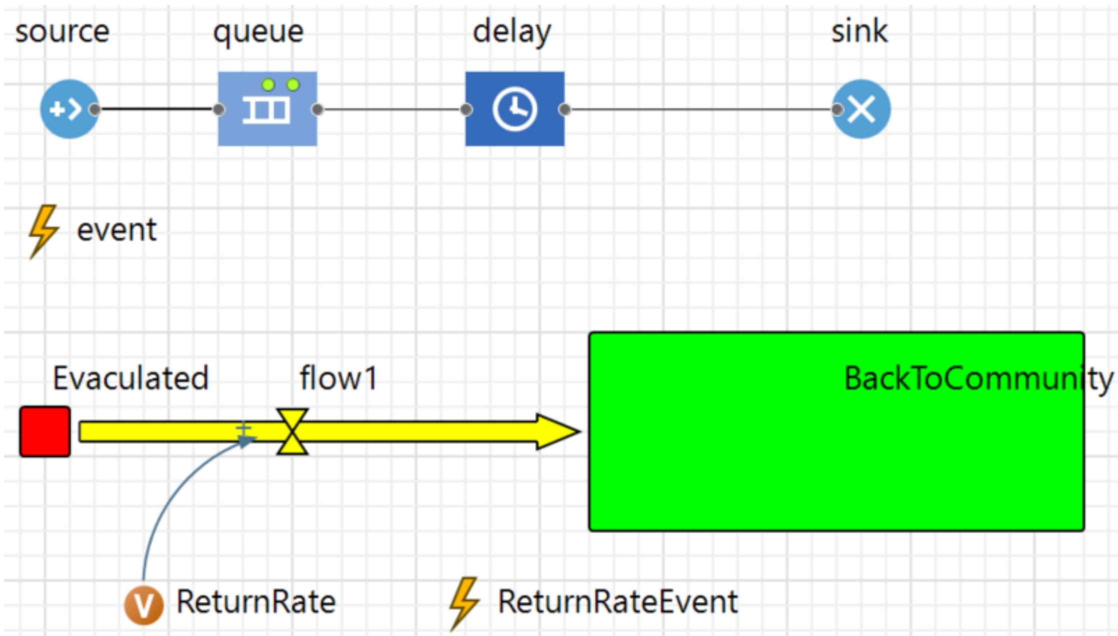


Figure 4-33 Debris generation process in a pickup location

The *TDMS* agent model includes multiple debris treatment processes (see Figure 4-34). The TDMS processing modeling represents debris pickup by truck and transportation to a TDMS. Debris separation (at the bottom left) describes the types of debris treatments available at TDMSs: chipping, no processing, and sorting for recycling. Two-time measurements (at the bottom right) are designed to identify and control the idle time of equipment during a simulation. Appendix#4 describes the details of model design and codes.

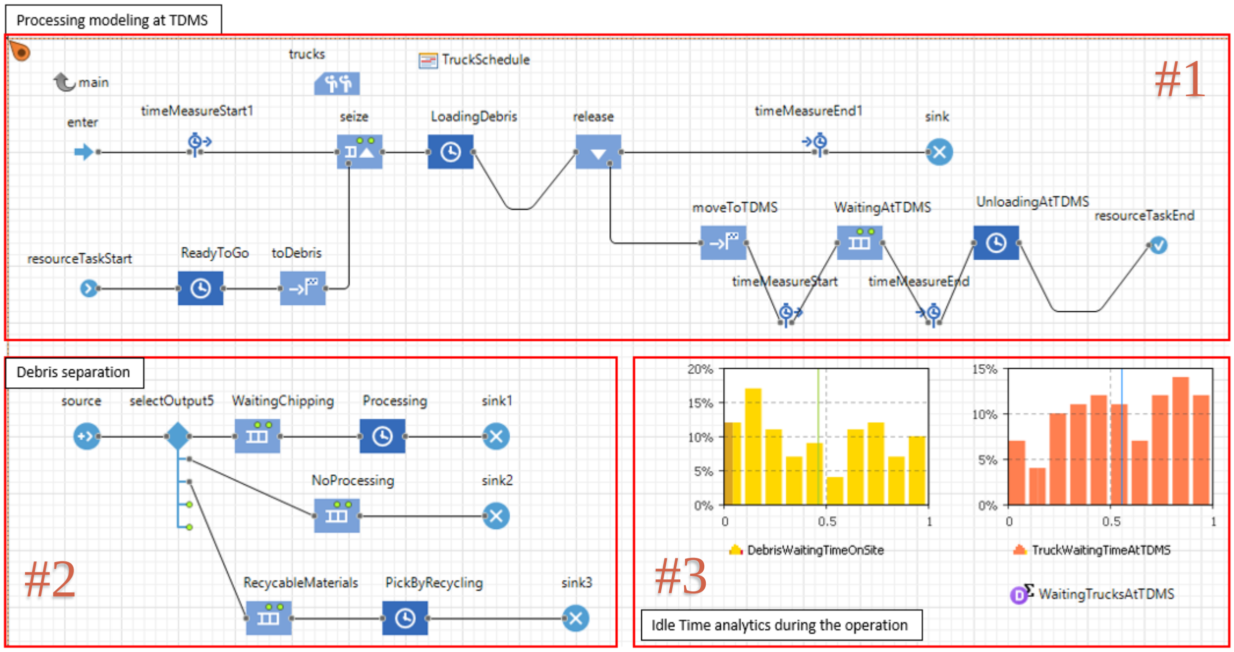


Figure 4-34 Processing model for *TDMS* agent

Note: #1 is a part of truck agent behavior (move -> load -> move -> unload -> move). #2 represents debris separation processes (e.g., sorting materials into chipping/grinding, no processing and transporting to recycling facilities).

In the case of a large hauling truck with 50 CY hauling capacity, it is designed to transport debris from TDMS to landfills: no type of post-processing in the landfills was considered in this study. *Batch* converts multiple *debris* agents into one agent (see Figure 4-35). A single *debris* agent represents 25CY of debris. Thus, a large truck *agent* hauls two debris agents (50CY debris) each time.

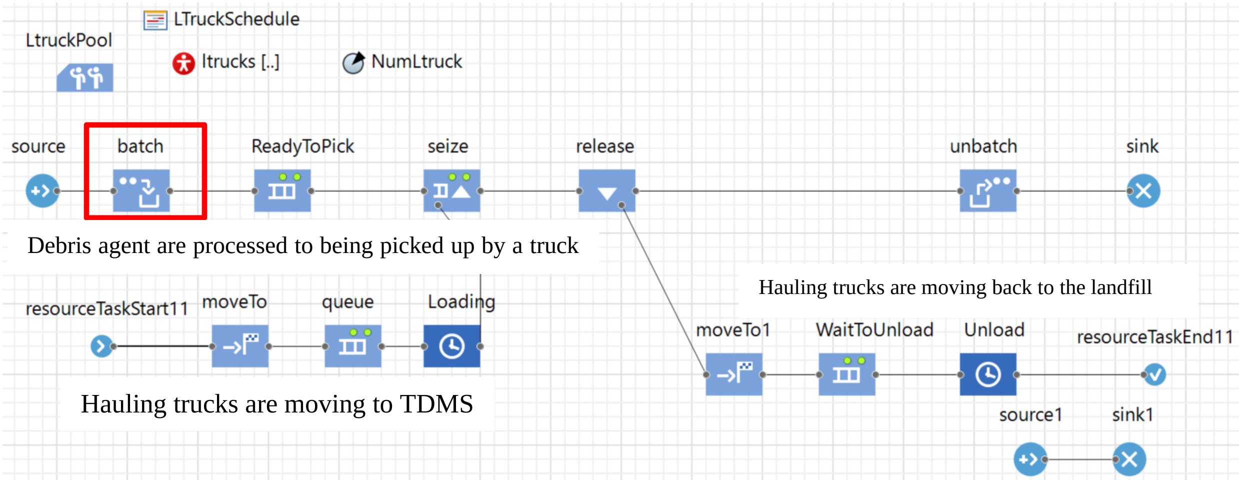


Figure 4-35 Agent behavior design of *Large hauling truck*

Note: LTruckSchedule refers to the operation time of trucks. For example, a user can define the operation time as being from 8 am to 5 pm. The agents are not in operation from 5 pm to 8 am the next day. Batch contains a certain number of debris agents.

4.3 Optimization

In ABM, an optimization experiment is vital when a decision maker needs to observe the complex debris management system behaviors under certain conditions and scenarios, and improve system performance. AnyLogic optimization is built on the top of OptQuest optimization engine (Laguna 2011). Thus, five steps are required to run an optimization experiment: 1) define parameters, 2) define objective functions (e.g. minimize or maximize objective functions), 3) define requirements and constraints, 4) specify a simulation stop condition, and 5) specify an optimization stop condition.

Parameters: Designated parameters in the optimization model are the number of small and large hauling trucks, loaders, and chippers for a TDMS and the amount of debris at a pickup site (see Figure 4-36). Users can define the minimum and maximum value for each parameter. *Step* refers to the parameter step in an experiment. *Suggested* refers to the initial value of the parameter.

Parameters:

Parameter	Type	Value			
		Min	Max	Step	Suggested
NumTrucks	int	150	250	5	220
NumLtruck	int	3	6	1	4
TdmsNu...aders	int	2	7	1	5
DebrisAtUnit*	fixed	800			
NumChipper	int	2	8	1	4
parameter	fixed				

Figure 4-36 Parameter settings in an optimization experiment

Objective function: The goal of optimization is to find the optimal parameters within available resources under given disaster scenarios to meet the objective function. An objective function is a mathematical expression to demonstrate the relationships of optimization parameters or the result of an operation (such as simulation) that uses the optimization parameters as inputs. $x_{i,j}^{truck}$ denotes the utilization rate of truck, i (25 and 50 CY) the truck type, and j the truck ID. The objective function formulated in this study is described below.

$$Maximize\ z = \sum_{j \in J} \sum_{i \in I} x_{i,j}^{truck} \quad \forall i \in I, \forall j \in J$$

Note: This was coded as root.tDMS.trucks.utilization() + root.LtruckPool.utilization().

The resource utilization rate is measured by *ResourcePool* (the icon and short description are in Figure 4-37).

- Double getUtilization(): returns the unit utilization, which is the fraction of time the unit was busy. The returned unit utilization value lies in the range [0, 1]. If the availability of the resource unit is defined in the ResourcePool block by a schedule, utilization will be calculated during the only designed operating hours of resource unit.

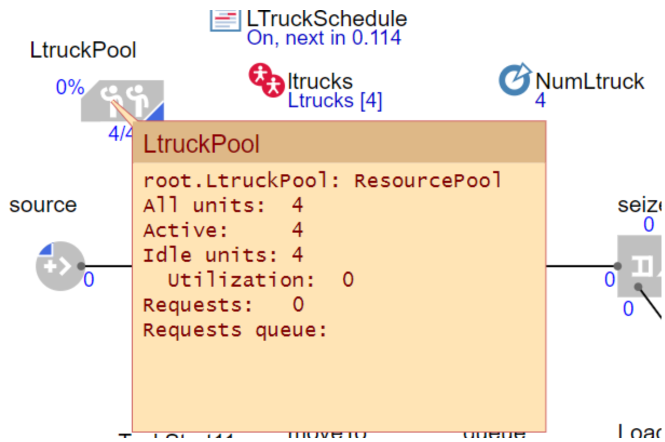


Figure 4-37 Resource utilization (e.g., large capacity truck)

Note: The total number of trucks in the resource pool (All units: 4). Currently, all units are in idle (idle unit: 4), and the utilization rate is 0.

Constraints and requirements: A constraint is a defined condition upon optimization parameters - each time the optimization engine generates a new set of values from a set of parameters for the optimization parameters, it checks whether these values satisfy the defined constraints. This reduces a searching dimension (i.e., space or a set of solutions). A requirement is defined as an additional restriction required for the solutions obtained from the optimization engine. Designged requirements are checked at the end of each simulation, and if they are not satisfied with constraints and requirements, then a set of parameters used in the specific simulation are rejected. This study assumed certain constraints and requirements for conducting simulation studies, including truck utilization rate, limit on the number of trucks inside a TDMS, and TDMS capacity (see Table 4-6).

Table 4-6 Constraints and requirements in the optimization model/simulation

Constraints	
TDMS capacity	<= 500,000 CY
Number of waiting trucks in TDMS	<= 50
Requirements	
Small and large truck utilization rate	>=0.6
% of debris removal within 90 days	>= 0.7

The idle time of resources (i.e., small and large hauling trucks) is measured by the time trucks wait in line to unload/load debris at debris pickup sites, TDMSs, and landfills (see Figure 4-38).

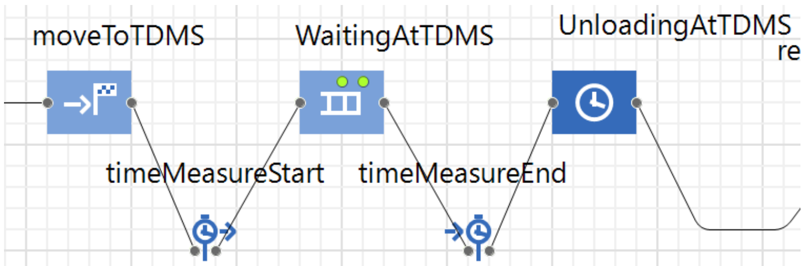


Figure 4-38 Time measurement function in TDMS

Note: timeMeasureStart and timeMeasureEnd measure time of resources in WaitingAtTMDS.

Simulation/optimization stop condition: By default, a simulation experiment in AnyLogic never ends. Thus, a user must define a stop condition for simulation and optimization experiments. The most common and simple simulation stop condition is "Stopping a simulation or optimization experiment at the specific model time". In the field of debris management, state and local emergency agencies have developed debris management strategies aimed at cleaning up generated debris within 90 days because FEMA's cost share for debris removal decreases over time.

Table 4-7 Alternative procedure for federal cost share

Debris removal work	Federal cost share
1-30 days	85%
31-90 days	80 %
91-180 days	75%

Note: Federal cost share is flexible based on the severity of a disaster. For example, 100% retroactive federal funding was approved to cover all debris removal costs, emergency protective measures, and direct federal assistance from Oct. 10 to Nov. 24, 2018 for disaster recovery efforts by Florida relating to Hurricane Michael (FEMA 2019b).

Thus, this study designed a simulation stop condition that ends the simulation after 90 days of debris removal operations (see Figure 4-39): *Stop* in *Model time* is set to *Stop at specified date* so that a simulation and optimization experiment is terminated at the designated date. In this study, the start and end dates are Aug. 10 and Nov. 8, 2016, respectively.

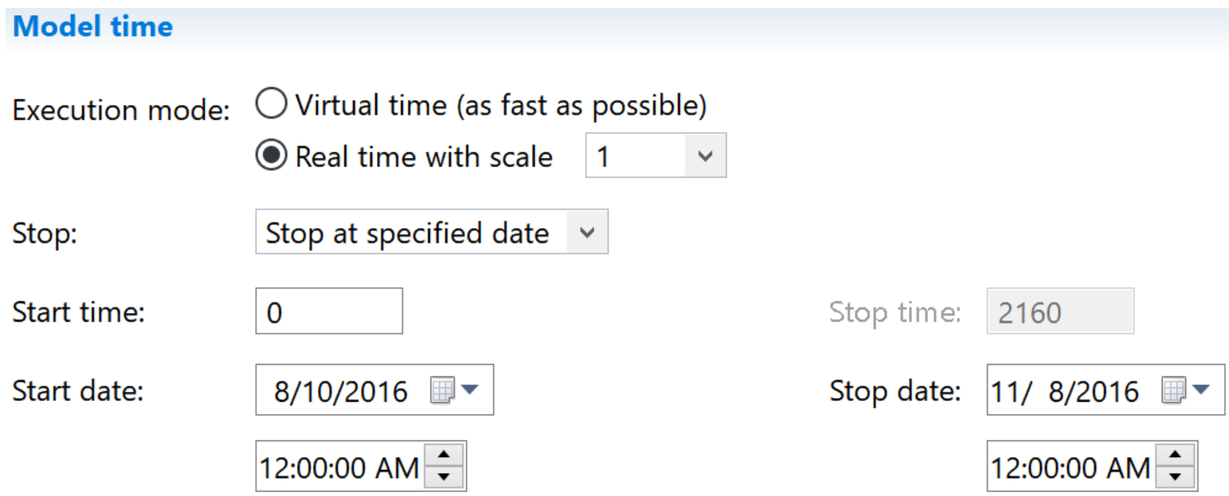


Figure 4-39 Simulation stop condition

Note: Real time with scale refers to setting the scale value (number of model time units executed per one second).

4.4 Graphical user interface in the adaptive DSS

Graphic user interface (GUI) is one of the critical components of ABM to visually examine the complex system behaviors under certain parameter setting and environments. The GUI in the adaptive decision support system consists of two parts: GIS map and system analytics (see Figure 4-40).

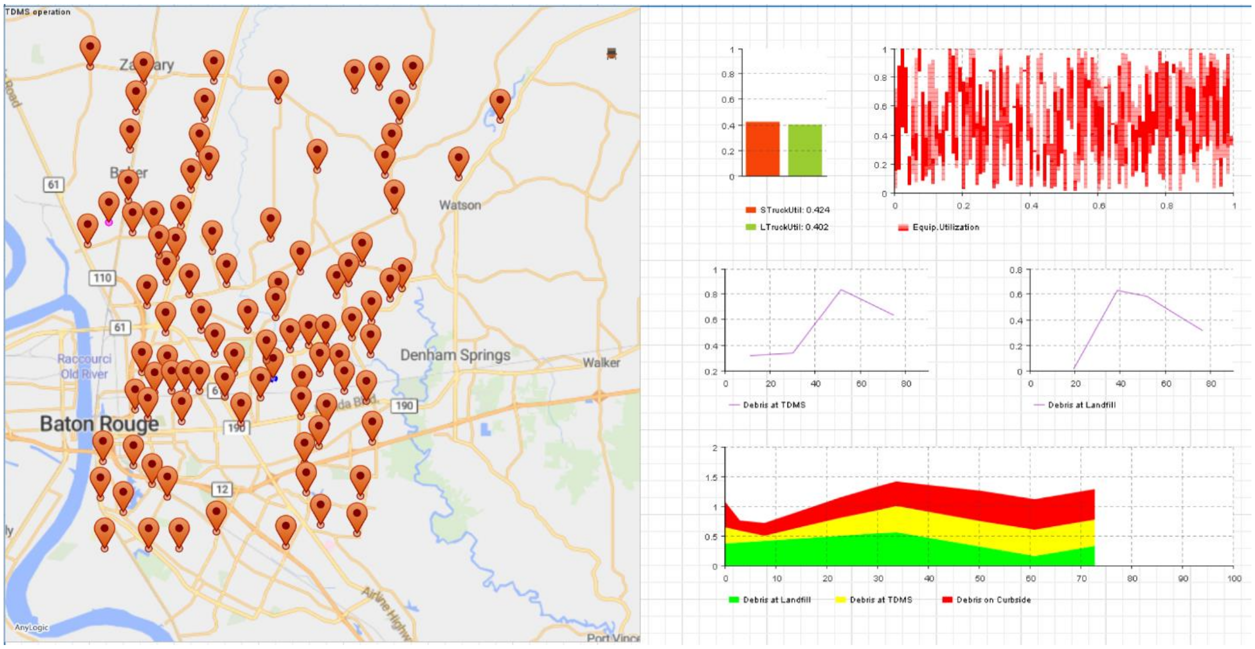


Figure 4-40 GUI in the adaptive DSS

Note: Red marks on the map refer to debris pickup locations, TDMSs, and landfills. On the right side, the bar graph on the top left represents small and large hauling truck utilization rates, and the line graph on the right represents utilization rates over time (x-axis = small truck, y-axis = large truck). The two-line graphs in the middle represent the amount of debris at TDMSs and landfills. The graph on the bottom represents current debris on the curb and at TDMSs and landfills.

To demonstrate the GUI, this study run a small-scale simulation and captured a screenshot on days#1,5,10 and 15. Table 4-8 describes the parameters and values applied in the experiment.

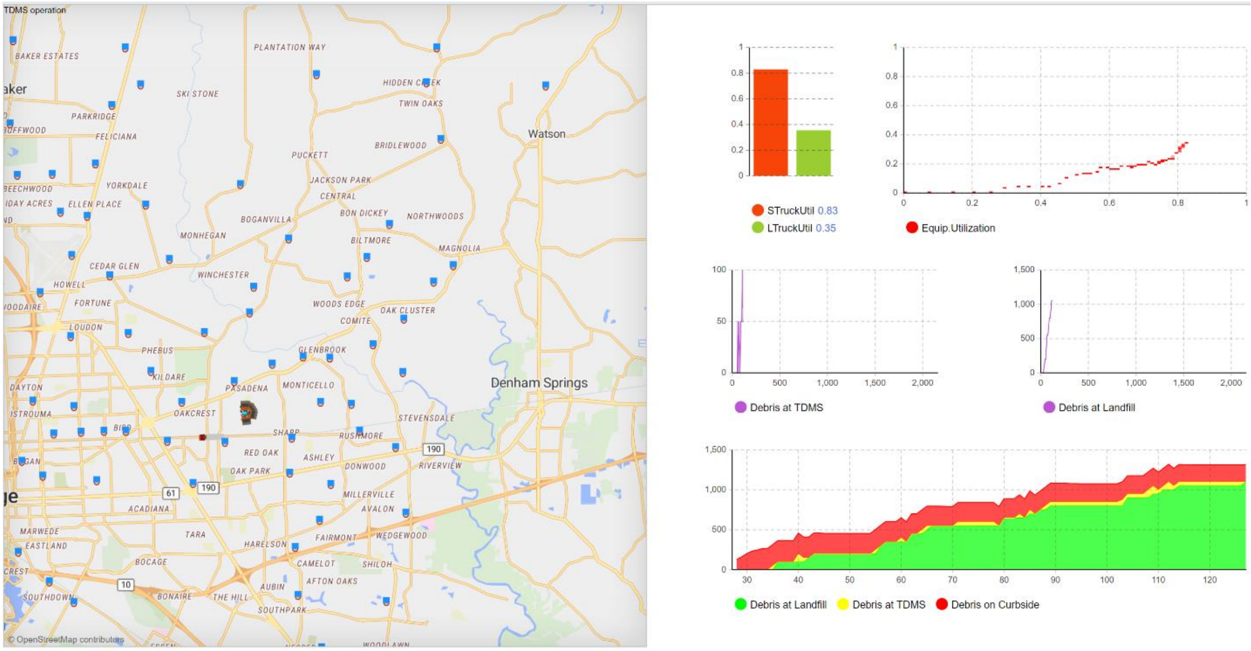
Table 4-8 Parameters in the simulation experiment

Parameter	Value	Notes
Amount of debris curbside	3	A single debris agent represents 25 CY. Value 3 refers to 75 CY of debris on each curbside
Small capacity truck (25CY)	5	-
Large capacity truck (50CY)	2	-
Loaders at TDMS	3	-
Chippers at TDMS	3	-

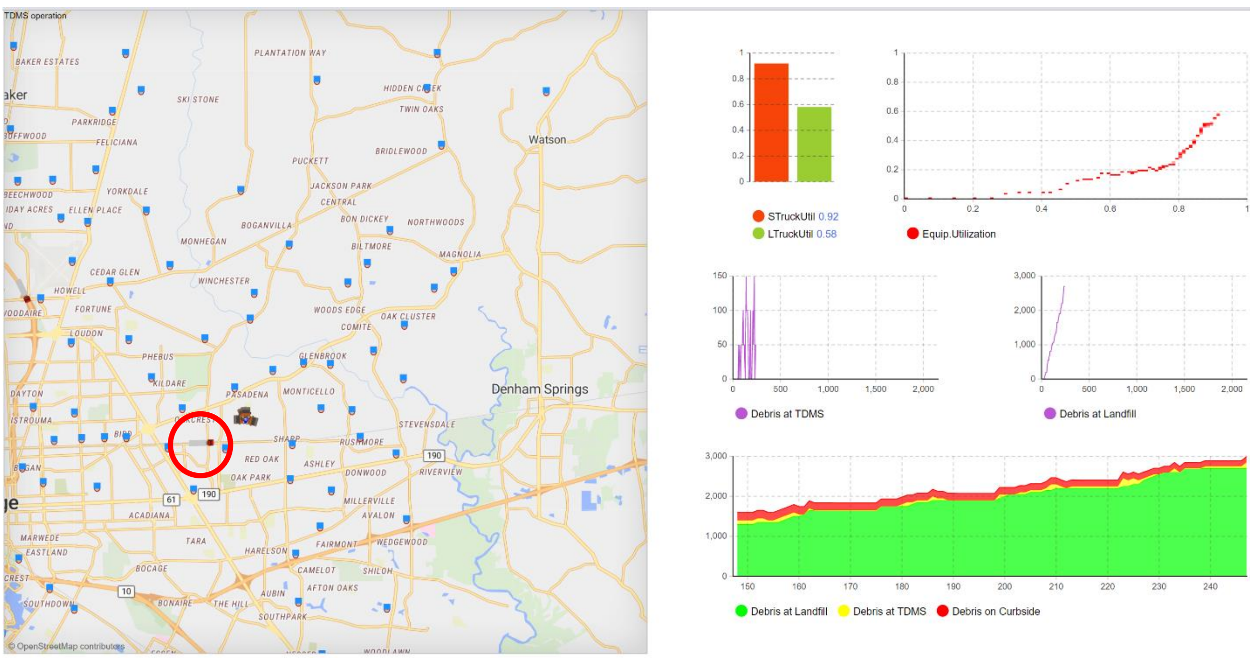
The following snapshots demonstrate how GUI is represented for a simulation experiment (see Figure 4-41 (a)-(d)). The blue squares on the map represent debris pickup locations.

(a) Snapshot of simulation experiment at day 1

Note: Small trucks are located at TDMSs – red circle on the GIS map. The amount of debris on the curb increases over time as people move generated debris from their properties to the curb. No values on the plots in the red-colored box because debris removal operation is not started yet.

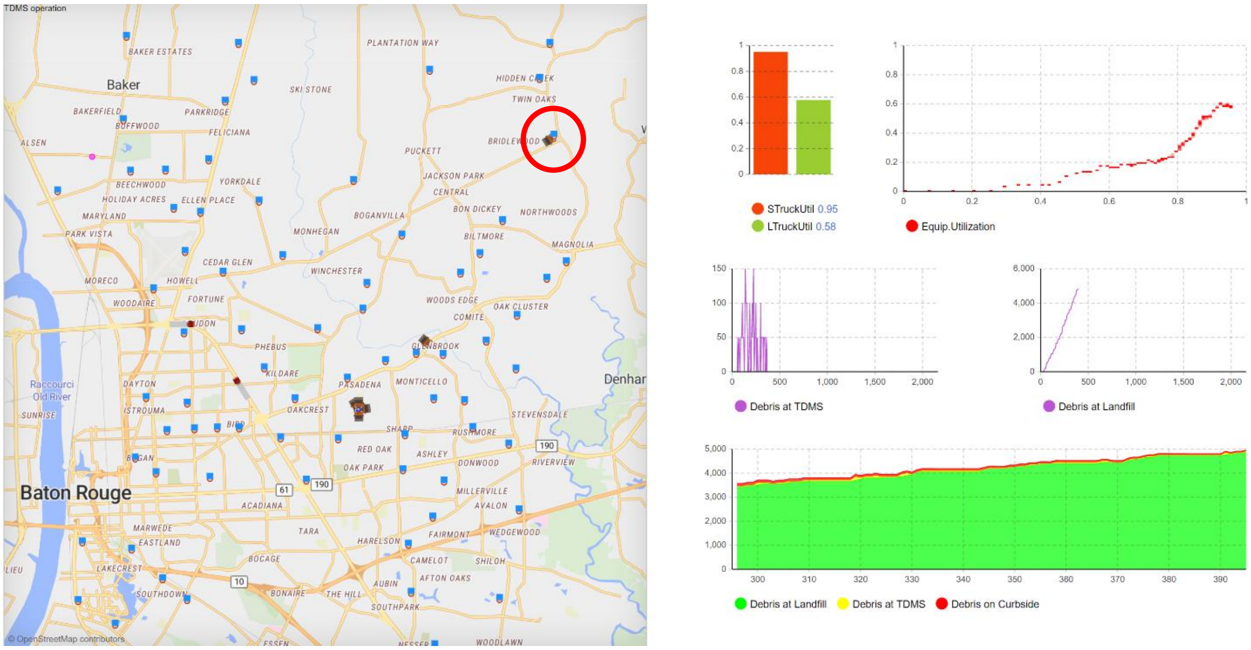


(b) Snapshot of simulation experiment at day 5



(c) Snapshot of simulation experiment at day 10

Note: Large capacity truck moves to TDMS to load debris – red circle on the GIS map.



(d) Snapshot of simulation experiment at day 20

Figure 4-41. Snapshots of simulation at days 1, 5, 10, and 20

Note: Small capacity truck picking up debris curbside – red circle on the GIS map.

Figure 4-42 shows the GUI for an optimization experiment. On the left side, a user can see the parameter inputs for each iteration. *Objective* refers to an output value of the objective function (objective function is described in Section 4.3). The *Best* column shows the best outcome and associated parameters from the iterations. On the right side, there are lines of three colors: gray, blue, and red lines. The gray line represents the value of the objective function's outcome. The red line represents the best value that does not meet the constraints and requirements before/after a simulation. The blue line represents the best outcome that meets all requirements and constraints.

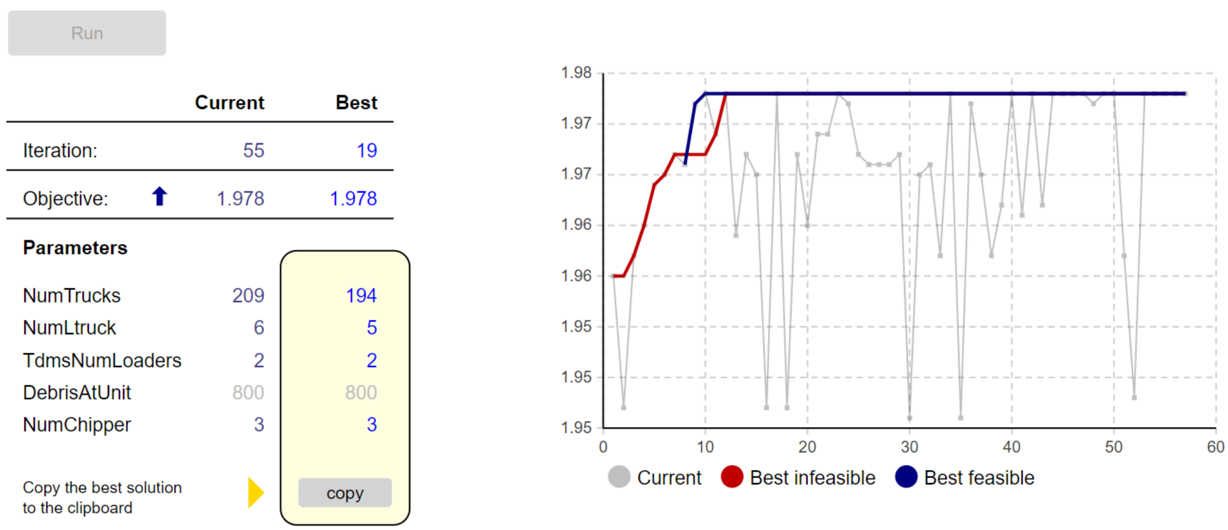


Figure 4-42 GUI for an optimization experiment

This computational experiment was conducted using a laptop with Intel Core i7-9750H @2.6 GHz, 6 core, 16GB ram. It took 5,362 seconds to complete 500 iterations to search optimal parameters and maximize the objective function (see Figure 4-43). Optimal parameters were determined to maximize the objective function value to 1.979 at the 269th iteration.

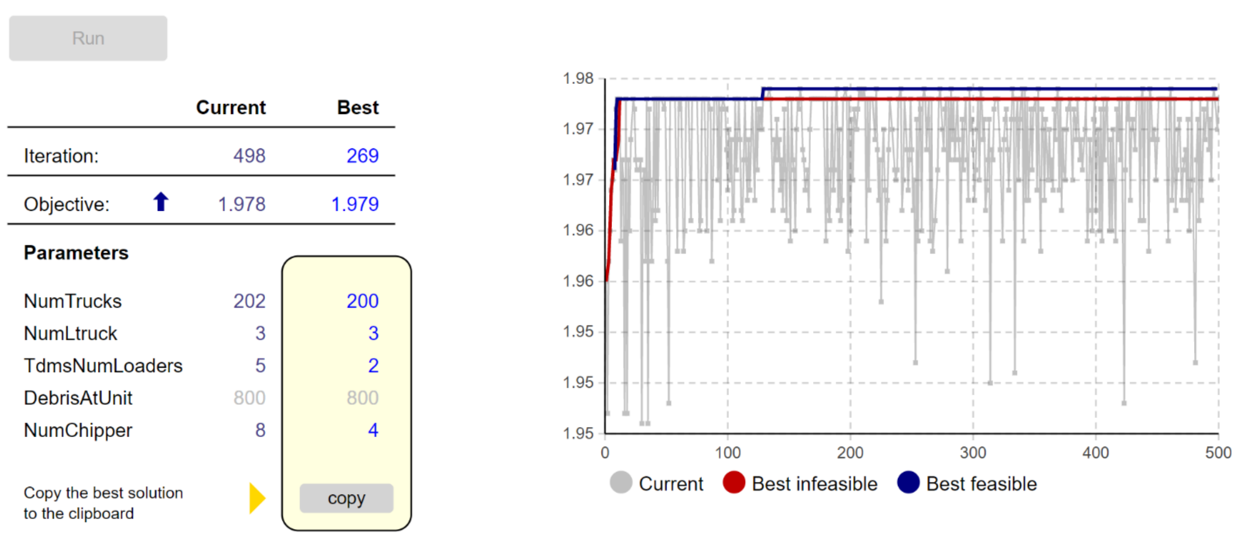


Figure 4-43 Result of an optimization experiment

4.5 Conclusion

This chapter discussed multiple methods and applications for Modules#1-4. To develop the proposed adaptive decision support system, it was critical to use a multi-method approach. This chapter discussed a GIS database for spatial data management, GIS-based spatial analysis for community structure analysis, TDMS design and selection, and ABM to simulate, understand, and optimize a complex post-disaster debris management system.

Further, this chapter discussed in detail the ABM development process, including critical elements of ABM, simulation, optimization, and the GUI. The ABM includes four types of agents: *debris*, *trucks*, *TDMSs*, and *landfills*. The agent rules were created based on the general debris management process (i.e., debris pickup, transportation, and treatment at TDMSs and transportation of debris to final destinations that include landfills, recycling, or other treatment facilities). An environment for the agents was created based on the information and data from Modules#2-3, including the road network and waste-related facilities. ABM simulations were performed using AnyLogic. The simulations were designed to simulate the behavior of debris management systems under certain scenarios. Multiple input parameters were designed, such as the number of small and large capacity trucks, the number of loaders and chippers at TDMSs, and the amount of debris generated in a scenario. This allows decision makers to run multiple scenarios before or after a disaster to examine existing debris removal strategies. This enables decision makers to examine total debris removal time, equipment utilization rates over time, and the amount of debris on curbs and at TDMSs and landfills over time. The optimization model was developed based on the objective function (to maximize the equipment utilization rates during debris removal operations). Several constraints and requirements were designed to make solutions more feasible in the real world, such as TDMS capacity, maximum equipment utilization rate (e.g., the rate cannot be 100%), the maximum number of trucks waiting in line at a TDMS (e.g., more than 50 trucks cannot wait in line). Finally, a GUI for simulation was developed to operate the adaptive decision support system in an effective manner. Users can observe the behaviors of the entire debris management system through the GIS-based GUI and track the behavior of a single agent (e.g., *debris* or *truck* agent) over time. This allows multiple agencies and parties to communicate and discuss disaster management planning and operations in detail.

As discussed here, the adaptive decision support system serves all levels of post-disaster debris management, including management, operations, and planning. It supports emergency agencies to make effective decisions about issues that may change rapidly and cannot be easily specified in advance (i.e., due to the uncertainty of disasters). For example, an emergency agency may be unable to use pre-identified TDMSs after a disaster because of road blockages or disconnected bridges. In this case, Modules#2-3 of the adaptive decision support system can identify optimal TDMS locations based on the circumstances existing after a disaster. Further, Module#4 can assist with optimal planning and operations with very limited availability of resources in a disaster-affected community. This multi-level support from the adaptive decision support system has numerous benefits for complex post-disaster debris management.

CHAPTER 5. APPLICATION OF ADAPTIVE DECISION SUPPORT SYSTEM

5.1 Introduction

This research applied a proposed adaptive decision support system, using a case study, to investigate the effectiveness of debris removal in the City of Baton Rouge after the 2016 Louisiana flood. The city's debris management strategies and practices were systematically reviewed in terms of debris estimation and classification, temporary debris management sites (TDMSs), and bottlenecks and other issues.

The 2016 Louisiana flood was one of the worst recorded disasters in the U.S., after Hurricane Sandy in 2012 (Yan & Flores 2016): The slow-moving storm generated extreme rainfall and historic flooding in multiple South Louisiana parishes. Within two days, more than two feet of rain was measured in certain areas: The highest rainfall recorded was 31.39 inches in Watson parish (see Figure 5-1) (The Weather Channel 2016; U.S. Department of Housing and Urban Development 2017).

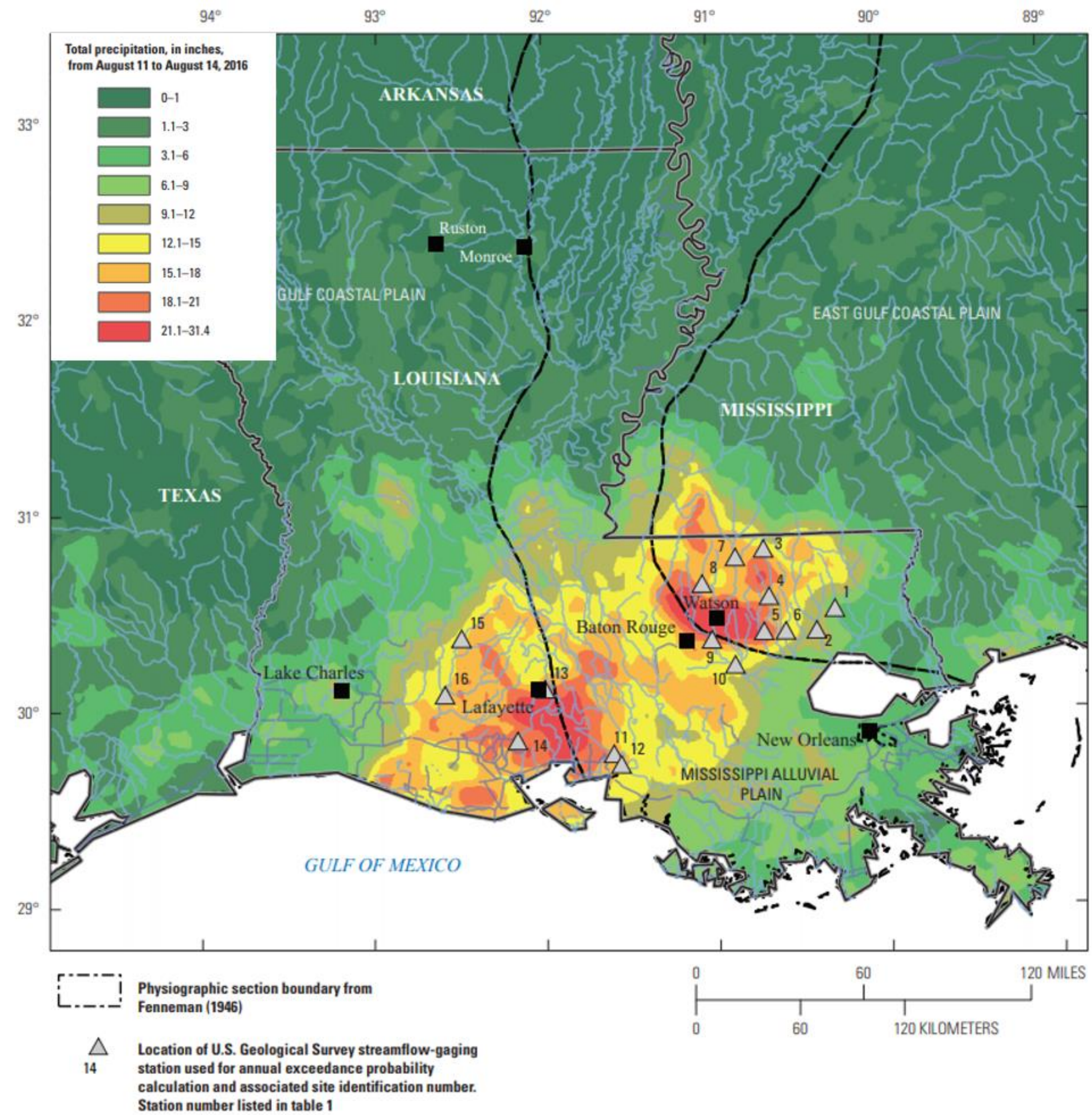


Figure 5-1 Cumulative rainfall during August 11 to 14, 2016

Note: USGS streamflow-gaging stations (gray triangles in the figure) were used to estimate annual exceedance probabilities.

Image from Watson et al. (2017)

Table 5-1 Total rainfalls during August 11-14, 2016 in Louisiana

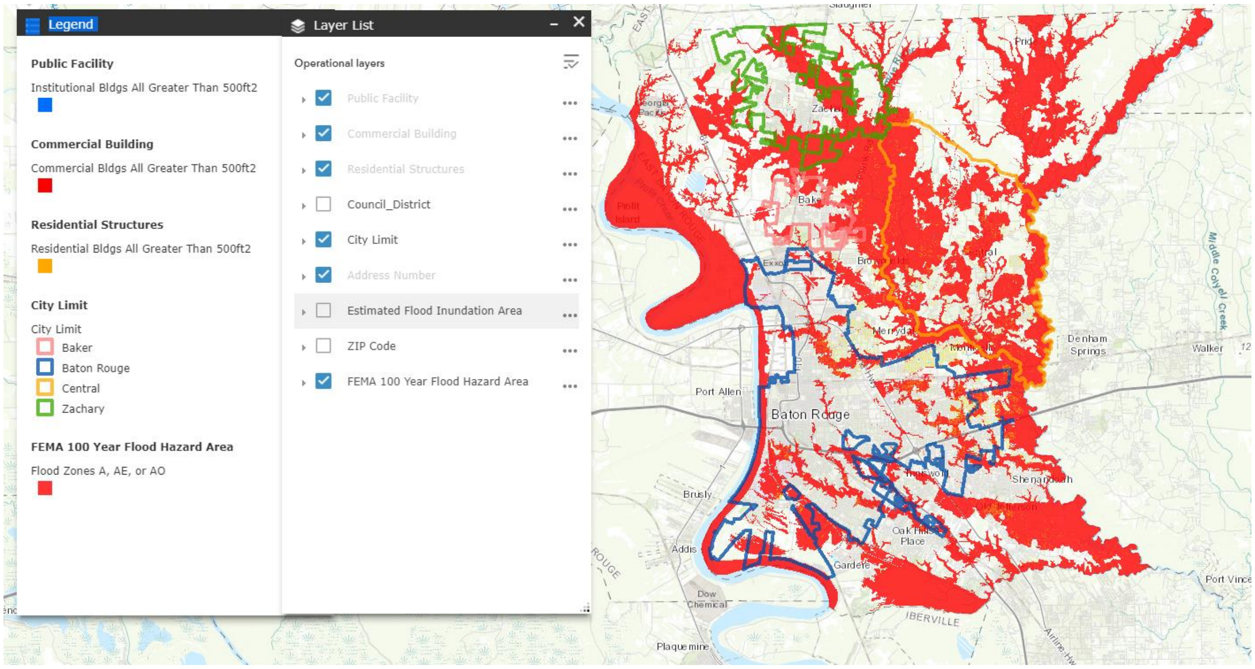
#	Location	Rainfall amount (inches)

1	New Roads 5 NE, Pointe Coupee Parish	16.07
2	Opelousas, St. Landry Parish, Louisiana	15.83
3	Baton Rouge Metro Airport, East Baton Rouge,	**18.07**
4	Livingston, Livingston Parish, Louisiana	**26.33**
5	LSU Ben-Hur Farm, Baton Rouge, East Baton Rouge Parish	13.07
6	Norwood, East Feliciana Parish	23.02
7	Pine Grove Fire Tower, St. Helena Parish	17.55
8	Ponchatoula, Tangipahoa Parish	8.61
9	St. Francisville, West Feliciana Parish	19.38
10	Abbeville, Vermilion Parish	19.05
11	Crowley 2 NE, Acadia Parish	16.96
12	Jennings, Jefferson Davis Parish	16.94
13	Kaplan, Vermilion Parish	15.23
14	Lake Arthur 7 SW, Jefferson Davis Parish	15.59
15	Donaldsonville 4 SW, Ascension Parish	15.59
16	Lafayette FCWOS, Lafayette Parish	21.35
17	New Iberia AP-Acadiana Regional, Iberia Parish	23.03
18	St. Martinsville, St. Martin Parish	25.10
19	Jeanerette 5 NW, Iberia Parish	17.88
20	Dutchtown #2, Ascension Parish	16.90
21	Gonzales, Ascension Parish	14.54

*Note: The information was reported from the National Oceanic and Atmospheric Administration meteorological stations (*https://www.ncdc.noaa.gov/data-access/land-based-station-data*).*

States and local agencies use information about flood zones to prepare disaster mitigation strategies and management practices. FEMA explains a special flood hazard area as an area having a chance of flood, equal to (or exceeding) 1% in an any given year: One percent flood chance is referred to as a base flood or 100-year floodplain. Figure 5-2 compares the 100-year flood zone with the estimated flood inundation area during the Louisiana flood: Multiple areas that were not in the 100-year flood plain were inundated, which are indicated by the blue-colored areas in Figure 5-2 (b).

(a) 100-year flood plain



(b) Estimated flood inundation areas

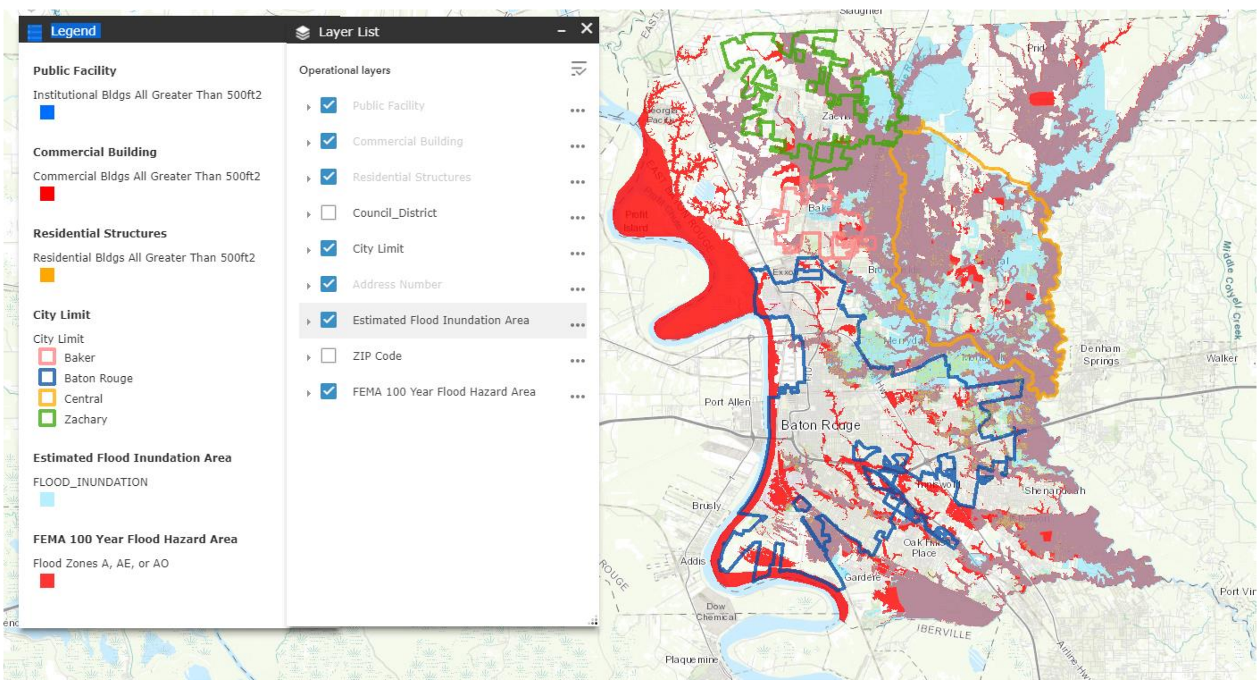


Figure 5-2 100-year flood plain vs. estimated flood inundation area during the 2016 Louisiana flood

Note: 100-year flood areas are represented in red. Inundated areas are represented in blue.

Flooding of numerous streams and rivers resulted in at least 13 fatalities and damage to more than 60,000 homes (Yan & Flores 2016). Monetary losses were estimated to be $10 billion across southern Louisiana and Mississippi (NCEI 2018; NOAA 2018). A couple of parishes in Louisiana used social media to share emergency information with people affected by the disaster. For example, the City of Baton Rouge actively used social media such as Facebook and Twitter to deliver real-time emergency information to affected people in a timely manner. The city operated real-time GIS maps to inform the community of estimated flood inundation areas.

The following section summarizes the overall debris management strategies and practices used in the City of Baton Rouge. In addition, multiple issues and bottlenecks that occurred during debris collection are discussed. This information is used as input data for a TDMS selection model as well as agent-based modeling for analyzing and optimizing the debris removal system.

5.2 Case study: Debris management in the city of Baton Rouge

5.2.1 Debris removal strategies and practices

To reduce the financial burden of debris removal on local governments, it is critical to have financial assistance and reimbursement from FEMA. During the flood, most of the parishes declared a state of major disaster. In Figure 5-3, parishes eligible to receive individual and public assistance are indicated in red, and parishes eligible for public assistance are indicated in orange.

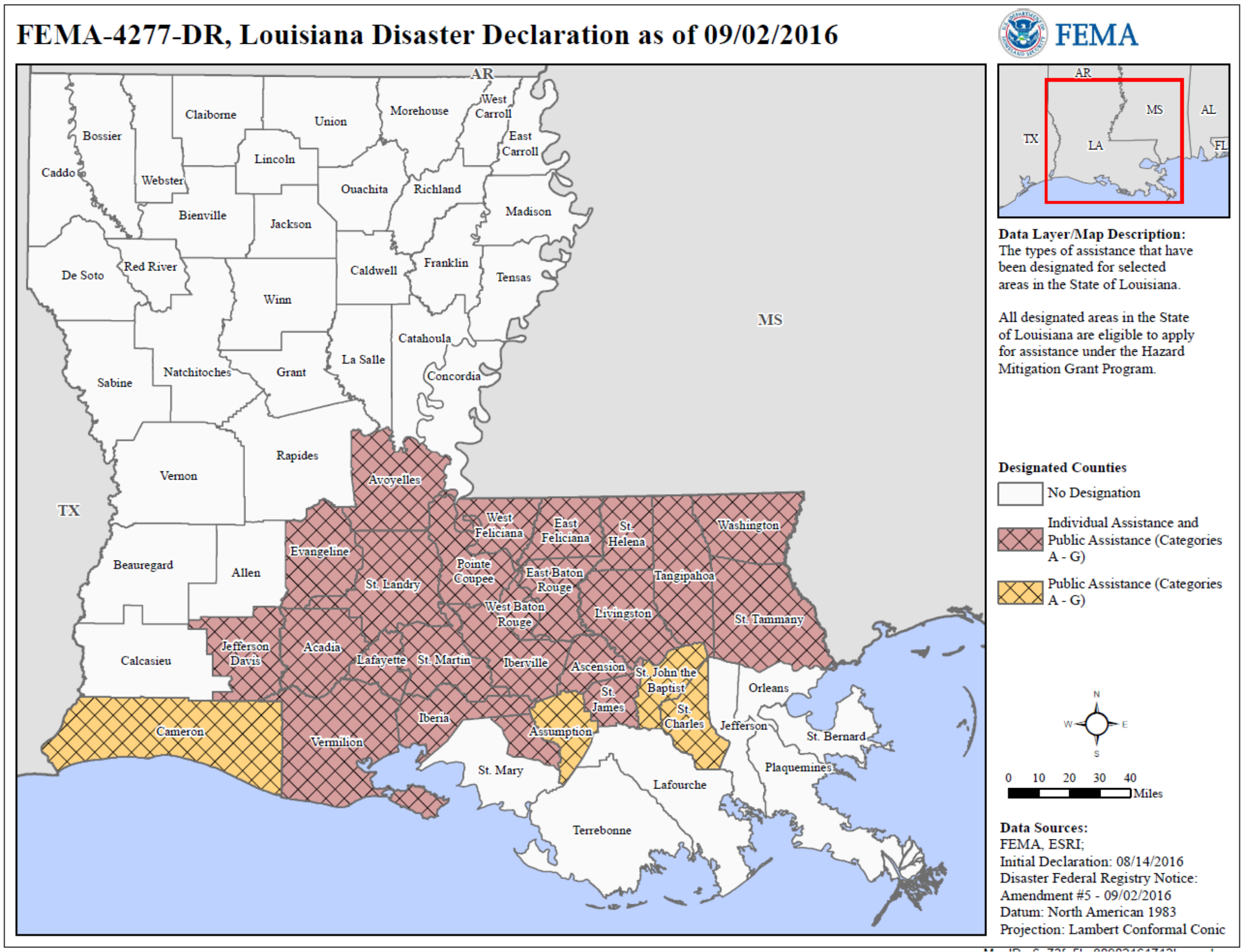


Figure 5-3 Louisiana areas declaring a major disaster on August 14, 2016

Note: The designated counties are Acadia (Parish), Ascension (Parish), Avoyelles (Parish), East Baton Rouge (Parish), East Feliciana (Parish), Evangeline (Parish), Iberia (Parish), Iberville (Parish), Jefferson Davis (Parish), Lafayette (Parish), Livingston (Parish), Pointe Coupee (Parish), St. Helena (Parish), St. James (Parish), St. Landry (Parish), St. Martin (Parish), St. Tammany (Parish), Tangipahoa (Parish), Vermilion (Parish), Washington (Parish), West Baton Rouge (Parish), and West Feliciana (Parish).

Reference: (FEMA 2016c)

FEMA approved around $535 million for public assistance (see Table 5-2). In general, public assistance grants can be used for emergency and permanent works. Emergency works include debris removal and emergency protective measures, and permanent works include the restoration of infrastructure and public facilities.

Table 5-2 FEMA assistance program statistics for Louisiana

Individual Assistance Applications Approved	83,104

Total Individual & Households Program	$776,923,661
Total Public Assistance Grants	$535,835,048

Reference: (FEMA 2016c)

For debris clean up, more than $88 million was approved for all eligible parishes (FEMA 2017b). FEMA planned to reimburse cities and parishes 75% of debris collection costs, with the remainder coming from local landfill funds or reserves. The volume of debris was estimated about 4.4 million cubic yards (CY). Three parishes, namely Ascension, East Baton Rouge, and Livingston, received the majority of funding for debris removal (see Table 5-3).

Table 5-3 Funding for debris removal from FEMA

Parish	**Total amount**
Ascension	$7 million
East Baton Rouge	$46 million ($6 million for Central)
Livingston	$25 million

Note: East Baton Rouge was the most flood-affected parish in LA.

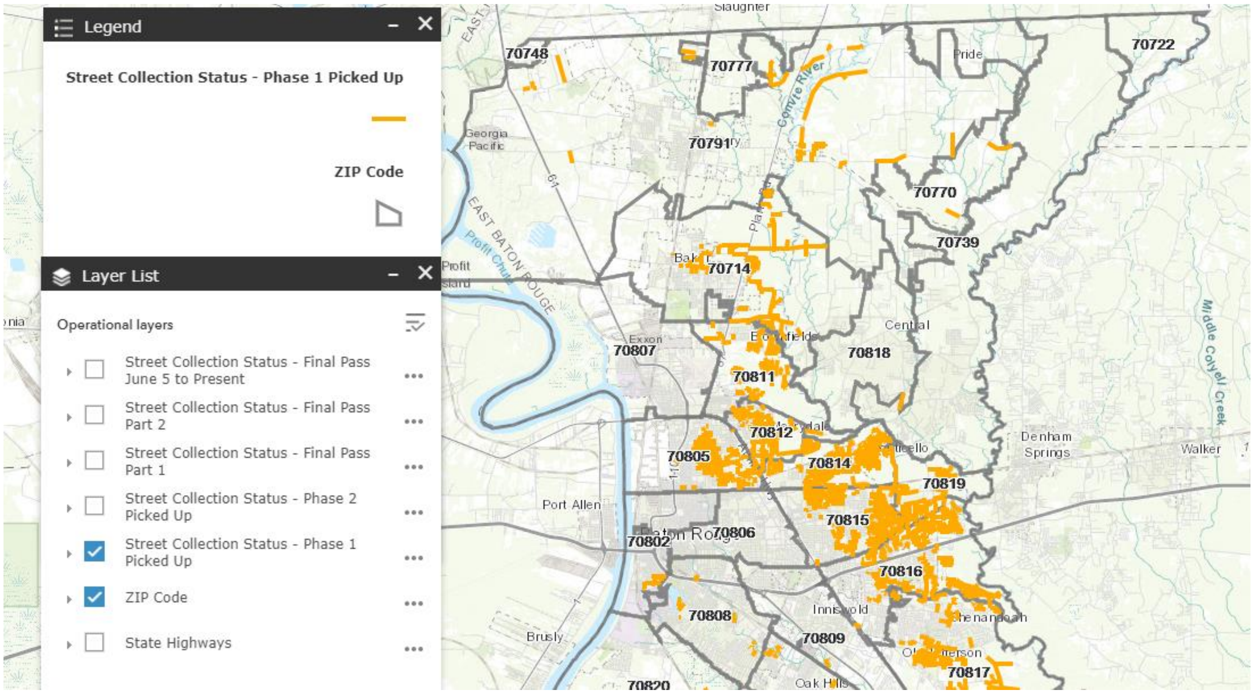
The City of Baton Rouge contracted with DRC Emergency Services, LLC to handle the debris generated. In the early stage of debris cleanup, DRC Emergency Services, LLC operated 20 trucks and estimated 90 working days would be required to make three passes through every neighborhood (Rosengren 2016). The estimated cost of debris removal was $5.6 million to transport 325,000 ~ 400,000 CY. The estimated amount of debris from one flooded house is up to 50 CY (Lau 2016a). For every cubic yard hauled, DRC made $13.98, plus $3.10 a cubic yard for processing at a temporary staging site, according to its contract. DRC hired five to six subcontractors who were paid $5/CY for debris pickup (Gallo et al. 2016). Each truck can haul between 100 ~150 CY of debris, and DRC estimated 6,000 CY as the amount of debris collected daily.

Residents in the City of Baton Rouge were asked to separate the debris generated from the flood and place it on curbside without blocking the roadway or storm drains. They were asked to avoid placing typical household trash with general debris on the day of debris pickup. Residents were asked to separate the debris generated into five categories.

- Vegetative yard waste (tree limb, leaves, etc.)
- Household chemicals, paint, herbicides, pesticides, caustic and flammable liquids
- White goods (refrigerators, washers, dryers, stoves, and similar appliances)
- Electronic appliances (computers, laptops, televisions, stereos, etc.)
- All other solid, nonhazardous waste/debris (building materials, furniture, etc.)

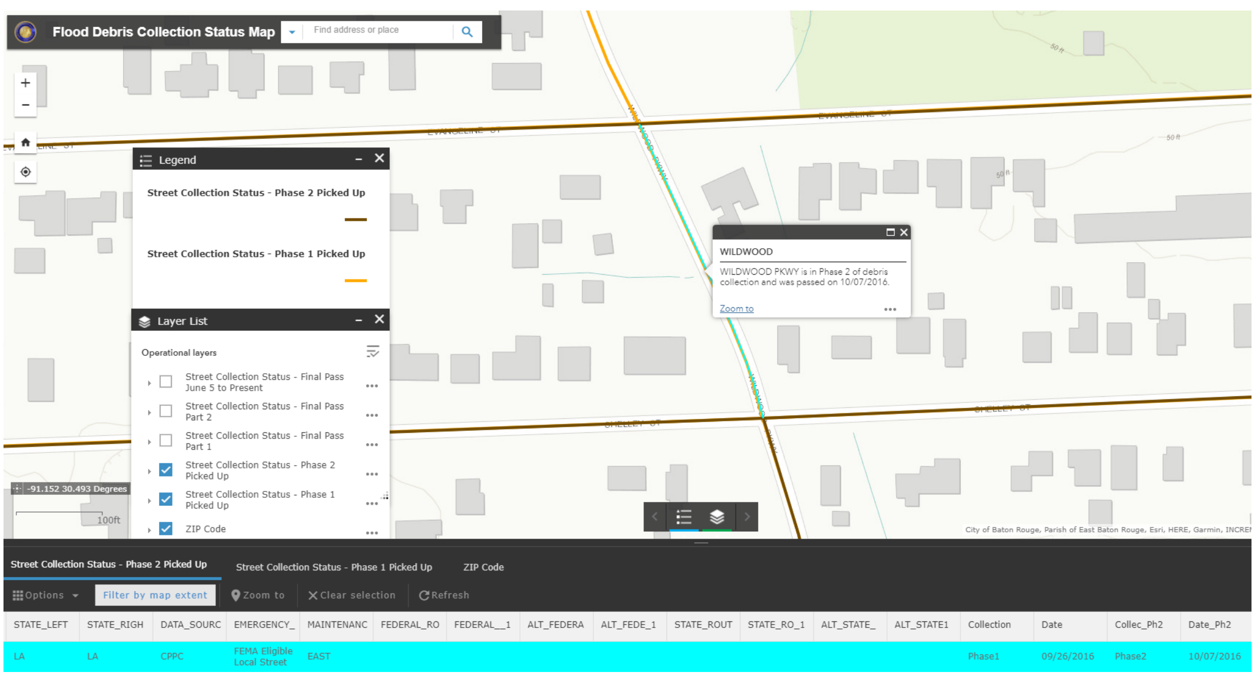
Social media was used as a communication channel. Residents were also encouraged to continue monitoring the City of Baton Rouge's social media channels such as Facebook or Twitter to receive updates on any progress made with debris collection along with announcements regarding subsequent zip codes to be serviced. In particular, the city uploaded their daily debris removal status on Facebook so that residents could easily access important information. The city also updated a GIS map with debris removal progress and the number of truck-passes (see Figure 5-4).

(a) GIS map for real-time debris removal status



Note: Yellow lines represent completed debris pickup during Phase 1.

(b) Example of information provided



Note: Users were able to check debris collection times for specific streets.

Figure 5-4 Flood debris collection status map

Images downloaded from CBR Facebook page

While the map was supportive to check the completion of debris removal in the city, it was not able to share upcoming debris collection efforts. Thus, residents were not able to know that when their debris/waste on curbside will be picked up.

5.2.2 Issues during debris cleanup efforts

While the existing debris management system in Louisiana was significantly enhanced due to experiences and practices after disaster recovery for the 2005 Hurricane Katrina, several issues were identified during debris management for the 2016 flood in terms of debris estimation, classification, waste-related facilities, and lack of equipment.

a. Debris estimation

Compared to other disasters, a flood results in a wide range of debris, including furniture, construction materials, and random water-logged waste. It can be somewhat difficult to determine the expected or current amount of debris because most of debris from floods is initailly inside of houses and facilities. Thus, errors in debris estimates after a flood can be higher than the other types of disasters. For example, in the city of Baton Rouge, the initial estimated amount of debris was 325,000 to 400,000 CY, and the expected total cost was about $5.6 million (Gallo et al. 2016; Rosengren 2016). The estimates continued to grow as people returned home and moved the contents of their houses to the curb. A week after the initial estimate, the City of Baton Rouge reported that the total amount of debris could be more than 800,000 CY (Lau 2016a). After a month, DRC reported that the amount of debris in the city was about 1.3 million CY. DRC operated 134 trucks, with an additional 30 added to increase the speed of debris removal in September 2016 (Gallo 2016).

Table 5-4 Changes in debris estimates in the city of Baton Rouge

Timeline	**Volume**	**Reference**
Immediately after the disaster	325,000 – 400,000 CY	(Rosengren 2016)
A week later	800,000 CY	(Lau 2016a)
A month later	1.3 million CY	(Gallo 2016)

b. Debris classification/separation

According to debris separation guidelines by the Department of Environmental Quality (LDEQ), construction and demolition debris does not include carpet, furniture, mattresses, and regulated asbestos-containing materials (see Figure 5-5).

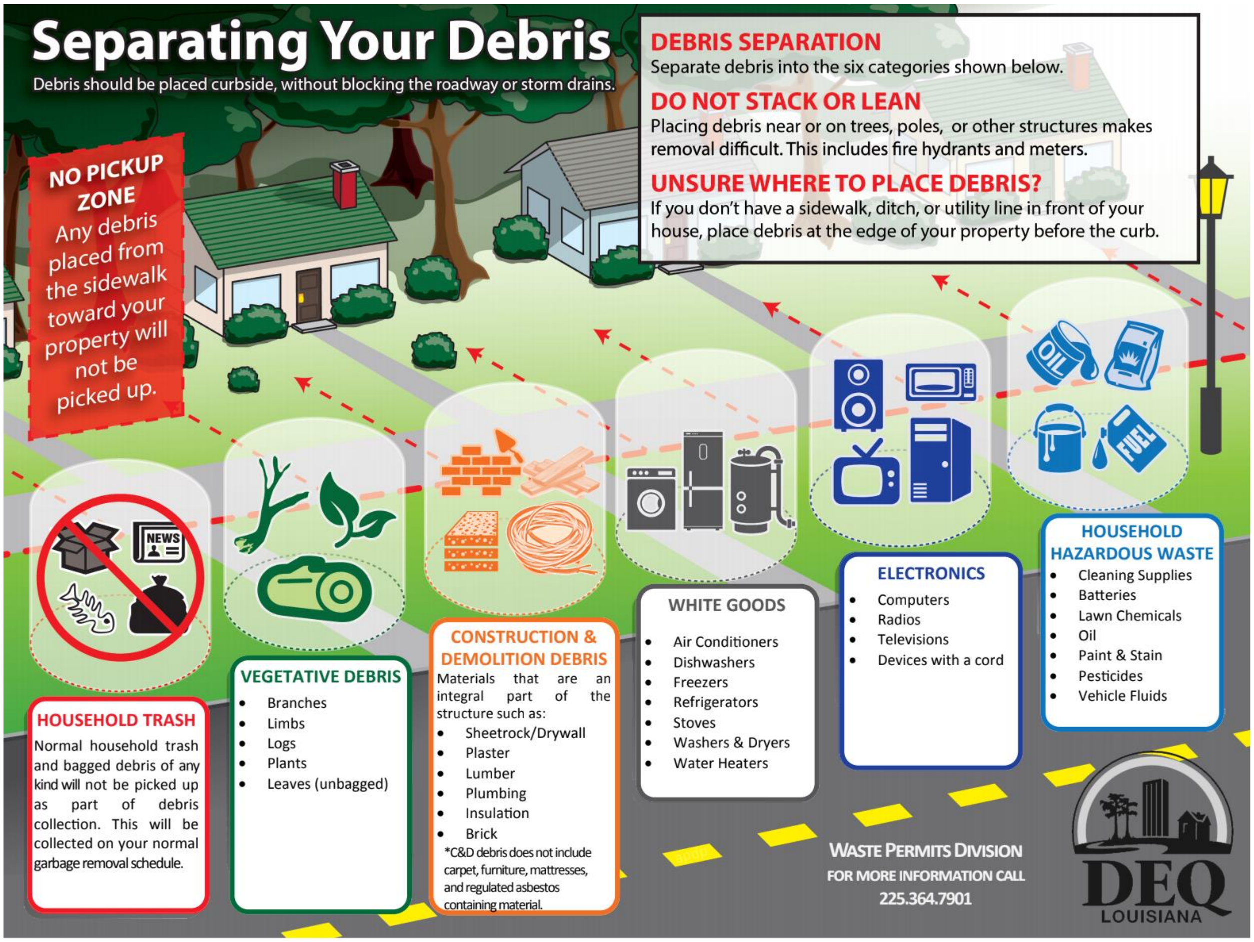


Figure 5-5 Guidelines for debris separation by LDEQ

Note: The orange-colored box outlines the construction and demolition debris category.

Image from Louisiana Department of Environmental Quality (deq.louisiana.gov)

As LDEQ did not update the definition of construction and demolition waste (C&D waste) to include mattresses and furniture, residents were required to separate those items and pace them in a household trash pile on the curb, as these items are sent to different landfills. This hampered overall debris removal performance (Rosengren 2016). LDEQ later issued an emergency order to include this debris with C&D waste (CBS 2016).

c. Capacity of waste-related facility

The capacity of waste-related facilities is designed based on the expected/reported amount of solid waste in normal conditions. After a disaster, the amount of debris is generally five to ten times greater than the annual average solid waste. Thus, multiple bottlenecks can occur during debris cleanup efforts, such as lack of capacity and equipment or reduced serviceability due to the road network.

For example, one landfill, Ronaldson Field, was not capable of handling the massive amount of debris, with some trucks waiting up to two hours to unload debris. Also, illegal debris dumping was reported by LDEQ, such as tires, carboard, mattresses, and appliances in a location other than a landfill (LDEQ 2017).

d. Concerns from residents

Most concerns surrounding debris management come from residents living near TDMSs and landfills and included the high volume of traffic and noise from trucks and special equipment such as chippers, grinders, and air incinerators. During debris removal in the City of Baton Rouge, similar complaints were reported. For example, residents near Ronaldson Field landfill complained that trucks caused heavy traffic and difficulty when travelling to receive medical services. They were also concerned that uncontrolled harmful materials might be buried in the landfill and cause future health issues (Lau 2016b). Residents near Ronaldson Field landfill and TDMSs were also concerned about the air quality during debris removal. Dermansky (2016) reported that LDEQ monitored air quality near the North and Ronaldson Field landfills but did not provide clear answers about air quality monitoring for the temporary debris management site.

5.2.3 TDMS operations in practice

As Ronaldson Field landfill was unable to handle the huge amount of debris input, the City of Baton Rouge decided to open two additional TDMSs (see Figure 5-6).

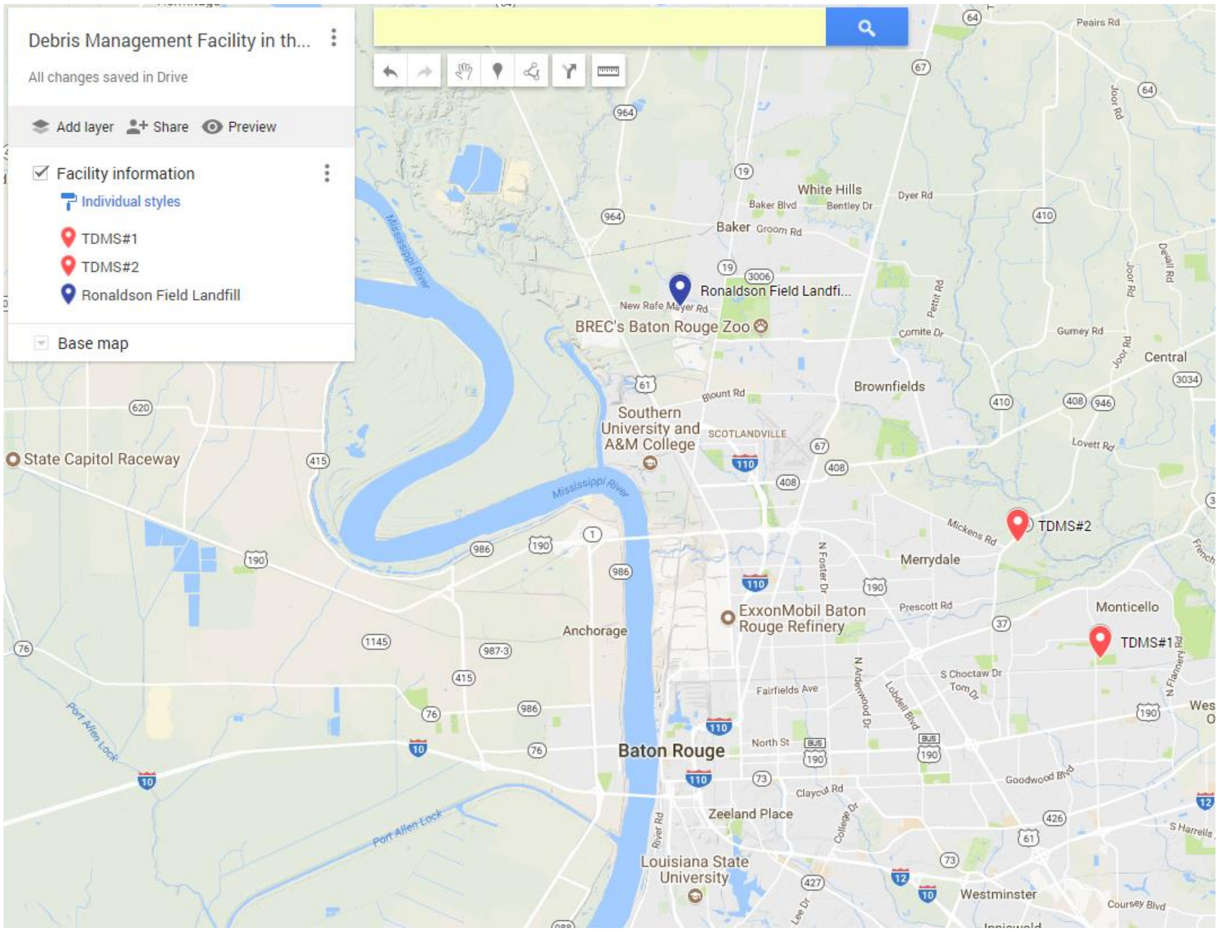


Figure 5-6 TDMS locations in the city of Baton Rouge

Note: The blue point represents Ronaldson Field landfill; the two red points represent the locations of TDMSs (TDMS #1: 2876 N. Sherwood Forest Drive, Baton Rouge, LA. 70814; TDMS #2: 6180 Joor Rd, Baton Rouge, LA, 70811).

These TDMSs were used to expedite debris removal. Debris in the TDMSs was then transferred to Ronaldson Field landfill or recycling facilities. The city expected to increase the speed of daily debris removal up to three times faster.

5.3 Method

This research conducts a case study of debris management in the City of Baton Rouge after the 2016 Louisiana flood to examine the performance of the proposed adaptive decision support system in terms of identification of TDMS locations, system behavior analytics, and system optimization. The required data and information were collected from the city's website and social media, USGS, the US Census Bureau, and the EBR GIS database. The basic assumptions are described in the followings:

i. The amount of debris generated after the flood was 1.3 million CY, and the density and location were estimated based on the Hazus-MH debris estimation results.
ii. There were no disconnected/damaged transportation networks in the city, and there were no reported physical damages on the transportation network after the flood.
iii. It is assumed that a truck agent speed (vehicle speed) was reduced to random [25,40] mile/hr and recovered up to random [35,50] miles/hr over time (e.g., random [25,40] generates a random number between 25 and 40 to define a truck agent speed for each trip).
iv. There were a sufficient number of loaders to load curbside debris into hauling trucks, so the number of loaders is not considered in this study.
v. The TDMS was designed with a maximum capacity of 1 million CY of debris. In addition, the maximum required number of TDMSs in the city is limited to two because the estimated debris generated in the city was 1.3 million CY.

Input parameters and constraints in the system optimization process are described in Table 5-5 Input parameters. Those parameter values and ranges were assumed based on the debris removal practices discussed in Section 5.2. Under the parameters, the optimization module in AnyLogic along with a scatter search by OptQuest, identifies optimal parameters to maximize the utilization rate of trucks to 85%.

Table 5-5 Input parameters

Type	Value*		Step**
	Min	Max	
Number of small trucks (Cap: 25CY)	150	250	1
Number of large trucks (Cap. 50CY)	3	50	1
Number of loaders at TDMS	2	7	1
Number of chippers/grinders at TDMS	1	10	1
Amount of debris on curbside	600	600	

Note: Min, Max and Step are designed for parameter variation during simulation experiments.
**Value refers to an input parameter for each simulation experiment. For example, the min and max value of the number of small trucks (cap:25 CY) is 150 and 250 respectively. It refers to the number of small trucks is between 150 and 250 during simulation experiments.*
***Step is a parameter step. For example, the number of loaders at TDMS will be 2,3,4,5,6, and 7 (step = 1) during simulation experiments.*

5.4 Results

5.4.1 Optimal TDMS locations

Based on the information and data related to the City of Baton Rouge, land suitability analysis was conducted to identify feasible locations of TDMSs for debris removal. To represent a score for each grid (performance score ranges from 5 – 12), this study applied multiple color hues (blue – white - red) for the performance scores (see Figure 5-7). The blue color hue was applied to represent grids with lower performance scores ranging from 5 to 9. The red color hue represents grids with higher performance scores ranging from 11-12. Areas (grids) with higher scores represent locations where satisfy existing TDMS regulations and policies such as avoidance of flooding areas, wetlands, and public facilities.

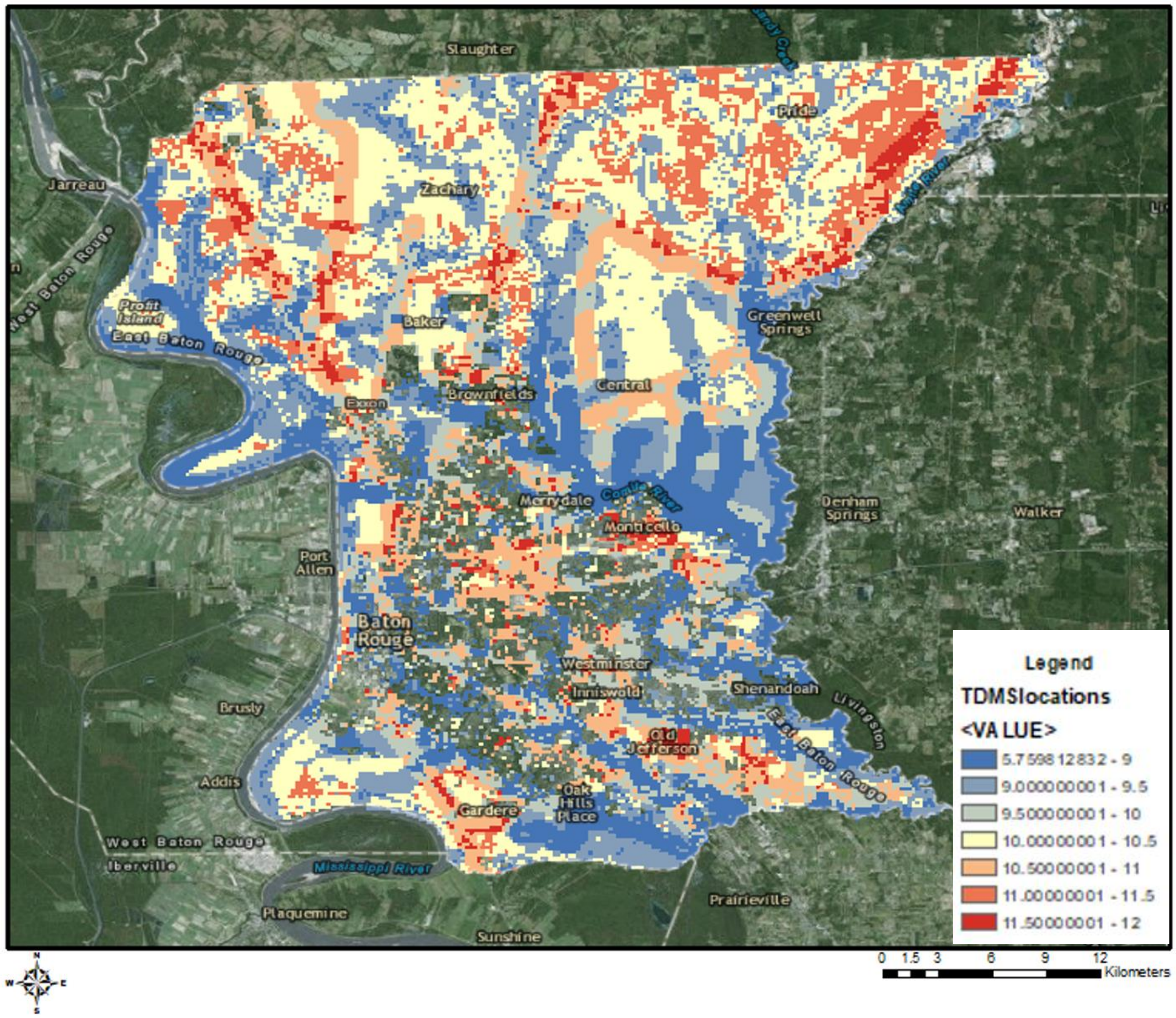


Figure 5-7 Visualization of performance scores by land suitability analysis in the city of Baton Rouge

Note: The performance score for each grid (ranging from 5 to 12) was represented by color hue (blue – white – red). The score of blue-colored grid ranges from 5 to 9 and the score of red-colored grid ranges from 11 to 12.

The areas with the highest scores are indicated with green-colored points (see Figure 5-8). To verify and validate the results, all criteria related to TDMS were manually examined for the selected areas. In addition, the selected locations were compared with satellite images from MS Bing Maps.

Satellite images of feasible locations

Satellite images of feasible locations

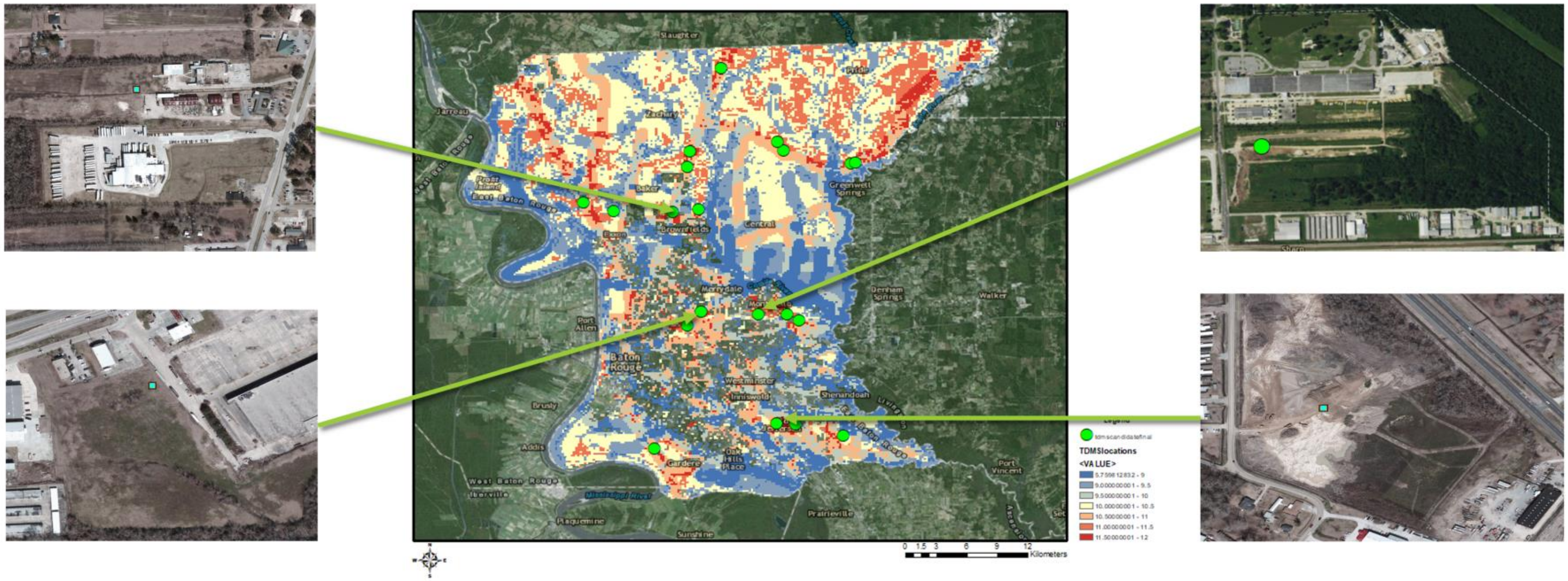


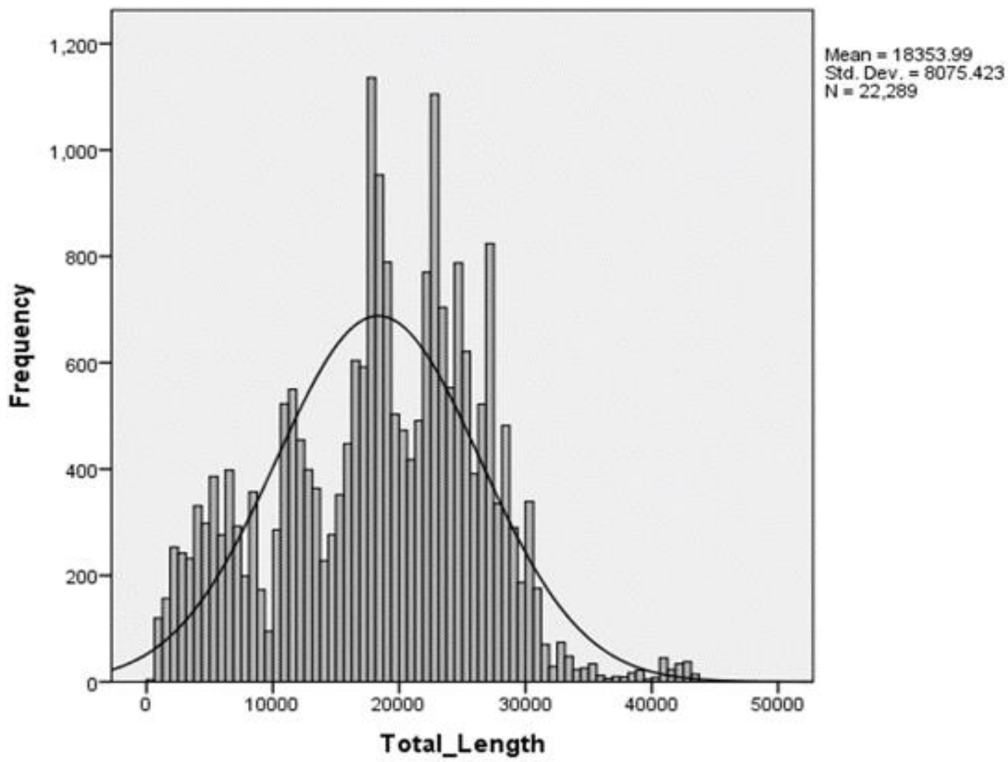
Figure 5-8 Identified feasible TDMS locations with satellite images

Note: Satellite images from MS Bing Maps (https://www.bing.com/maps).

Three different scenarios were developed based on debris removal strategies in the City of Baton Rouge in 2016. In the beginning of debris cleanup, the city operated the landfill to collect the debris generated and then opened two additional TDMSs to enhance debris removal performance. As the estimated amount of debris was 1.3 million CY in the City of Baton Rouge, this research assumed that a maximum of two TDMSs were required in addition to the existing landfill.

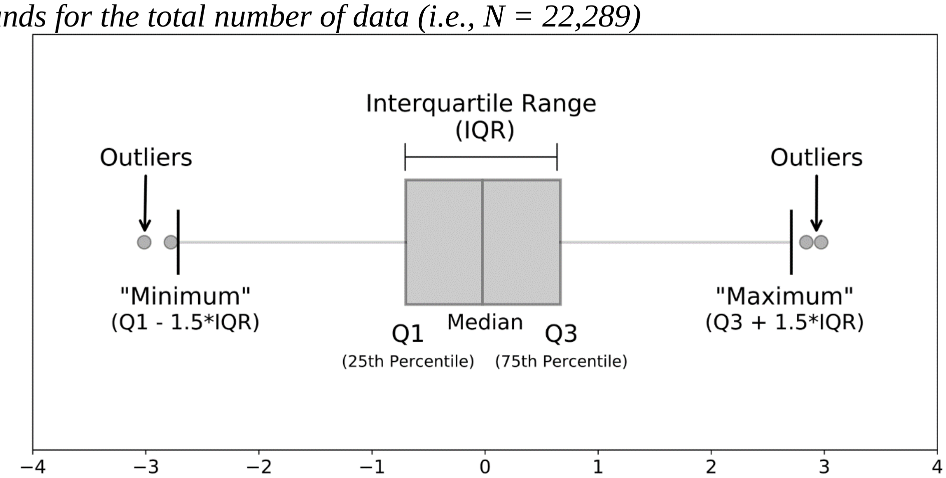
(a) Scenario #1: Operating a landfill only, without a TDMS
(b) Scenario #2: Operating a landfill with one TDMS
(c) Scenario #3: Operating a landfill with two TDMSs

A result of Module#3 is represented on a GIS map, and spatial data were analyzed by statistical tools including a histogram and box plot. A histogram represents a distribution of debris from a selected TDMS (see Figure 5-9). The x-axis represents a total distance (*i.e.,Total_Length*) measured by the existing road network (from TDMS to the debris pickup location). The y-axis represents the number of debris pickup locations are in each bracket. The line on the histogram is called a trend line describing the approximate shape of the debris' distribution in a community. A box plot is also a graphical method of displaying variation in a set of debris distribution data. While a histogram analysis provides enough information on the characteristics of debris distribution, a box plot can provide additional details such as minimum, first quartile, median, third quartile, and maximum.



(a) histogram

Note: N stands for the total number of data (i.e., N = 22,289)



(b) Box plot (image from towardsdatascience.com)

Note: Interquartile range (IQR) is the width of the box measured by $IQR = Q_3 - Q_1$. *Outlier is any value that lies more than 1.5 times of the length from either Q1 and Q3. Min and max are determined by* $Q_1 - 1.5 * IQR$ *or* $Q_3 + 1.5 * IQR$ *respectively.*

Figure 5-9 Histogram and box plot to understand the characteristics of debris distributions

The following figures demonstrate the average distance and standard deviation (SD) to the TDMSs.

In Scenario #1, the average distance and SD are 18.3 km and 8 km, respectively. In Scenario #2, the average distance and SD to are 14 km and 8 km, and to TDMS #1, they are 7 km and 6 km, respectively.

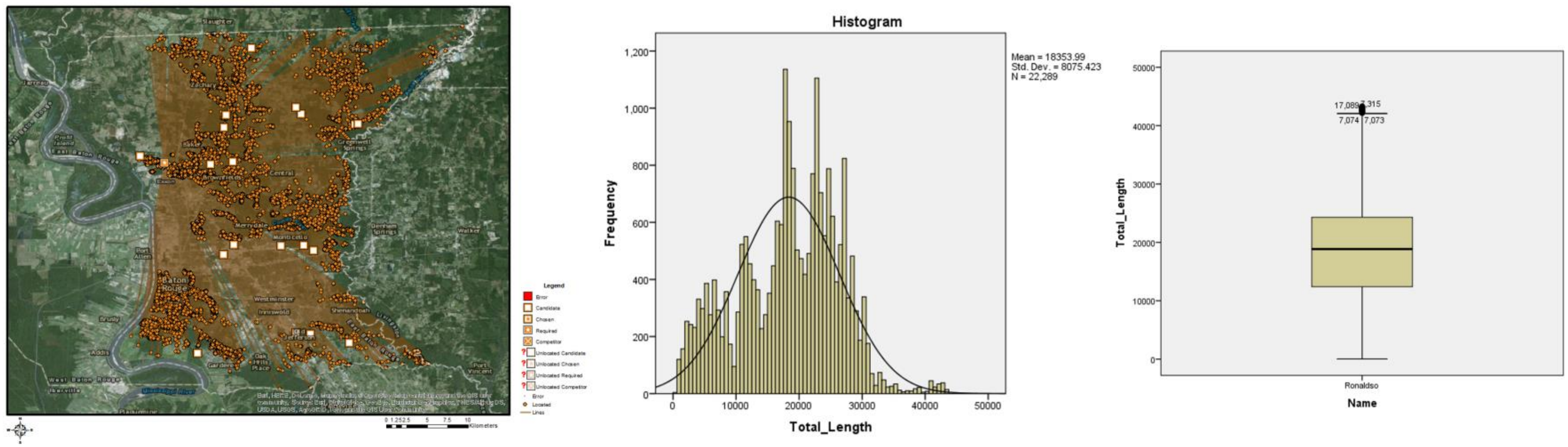


Figure 5-10 Results of Scenario #1

Note: The location marked with the orange star refers to the landfill: In the beginning of the debris cleanup process, the city transported the collected debris to this location.

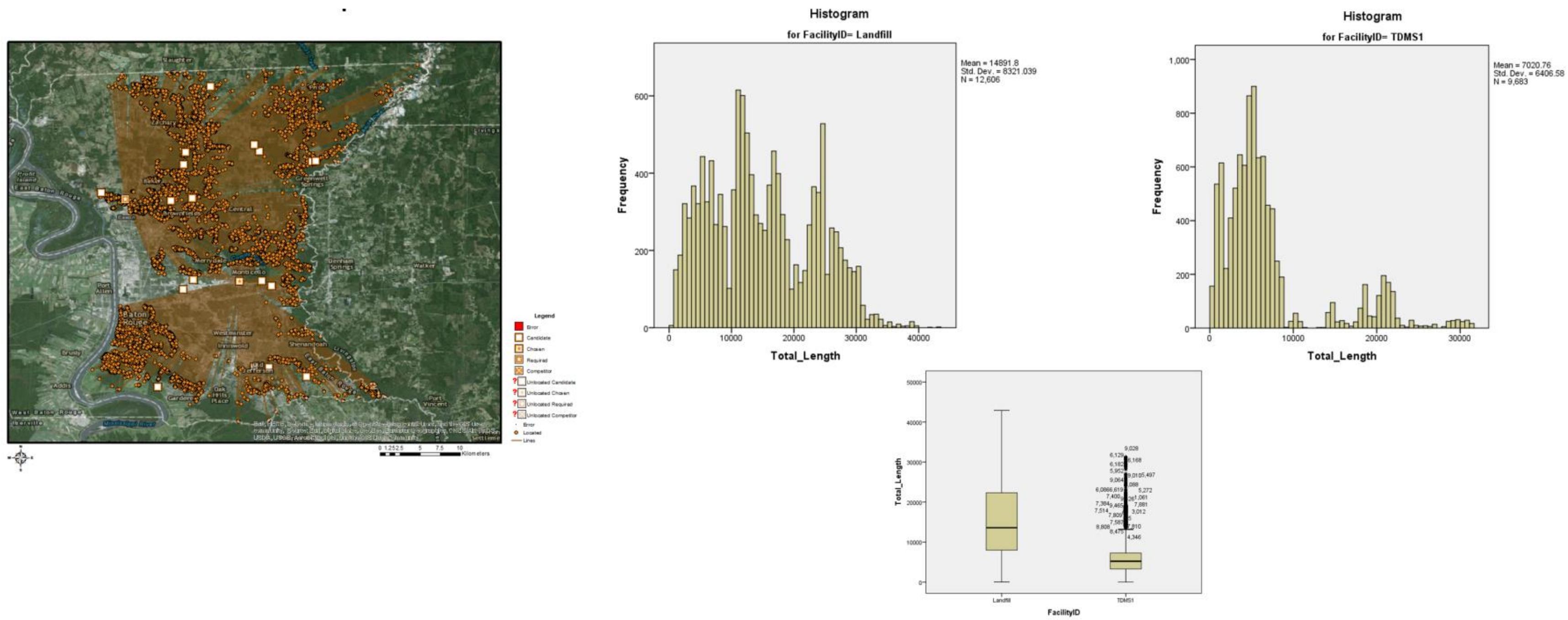


Figure 5-11 Results of Scenario #2

Note: the optimal location of a TDMS is in the center of the city.

In Scenario #3, the average distance and SD for the landfill, TDMS ,#1 and TDMS #2 are 4 km and 2 km, 13 km and 7.8 km, and 10 km and 6 km, respectively.

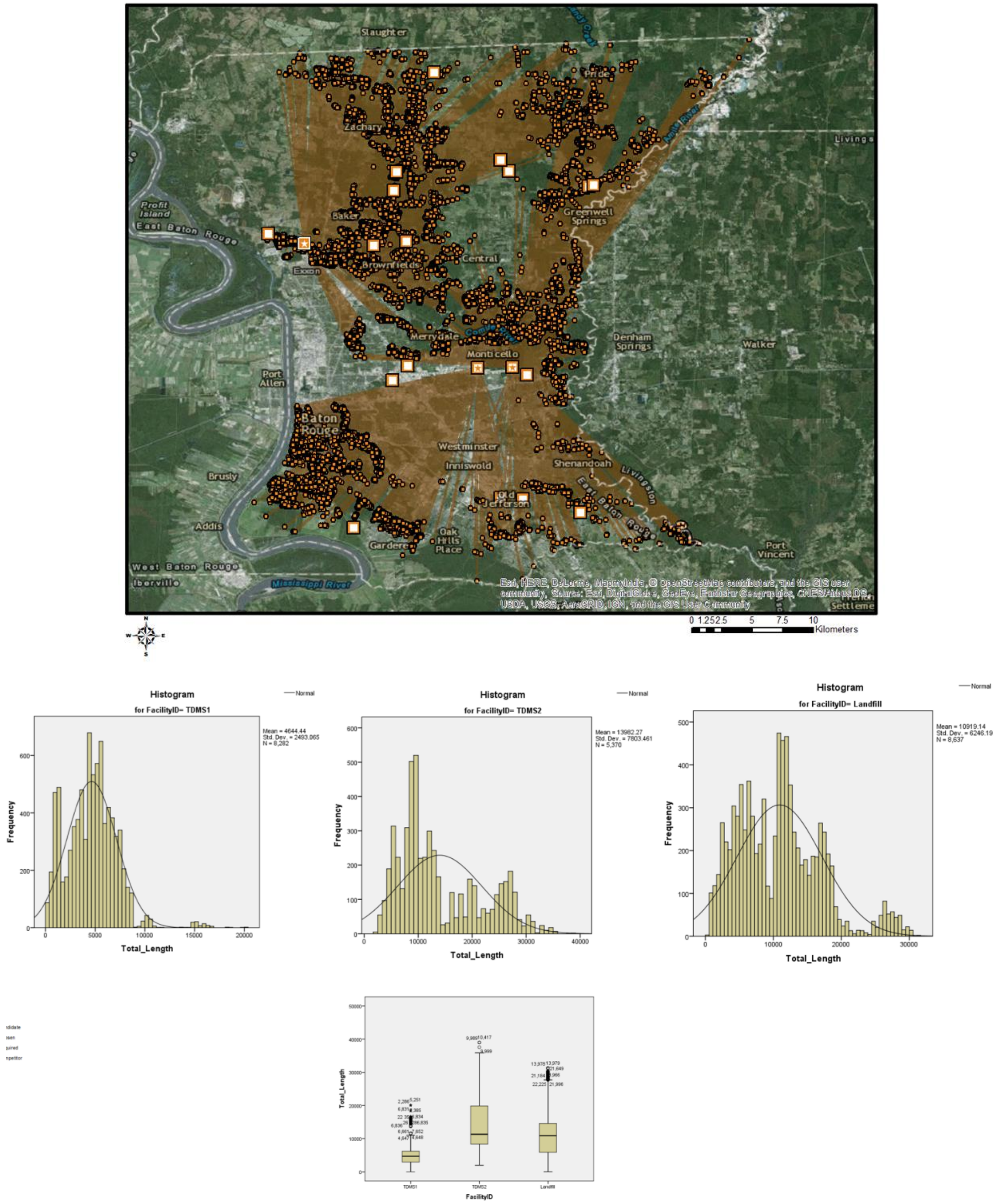


Figure 5-12 Results of Scenario #3: one landfill and two TDMSs

The results of the three scenarios are shown in Figure 5-13. The average distances and SDs for the results illustrate the positive impacts of siting additional TDMSs for debris removal. In Scenario #1, the distance from the landfill to debris sites is too great, with an average distance of 18.3 km and SD of 8 km. According to the Advocate™ (Louisiana's newspaper), it takes around two hours for a truck to load, transport, and dump debris at a landfill. This translates into no more than four loads/day/truck (Lau 2016c). By locating two TDMSs, the average hauling distances from TDMMs to the landfill were reduced to 14 km and 10 km, respectively. In addition, the lower SD provided more stable debris input into the TDMS by reducing the variance in the travel time of trucks.

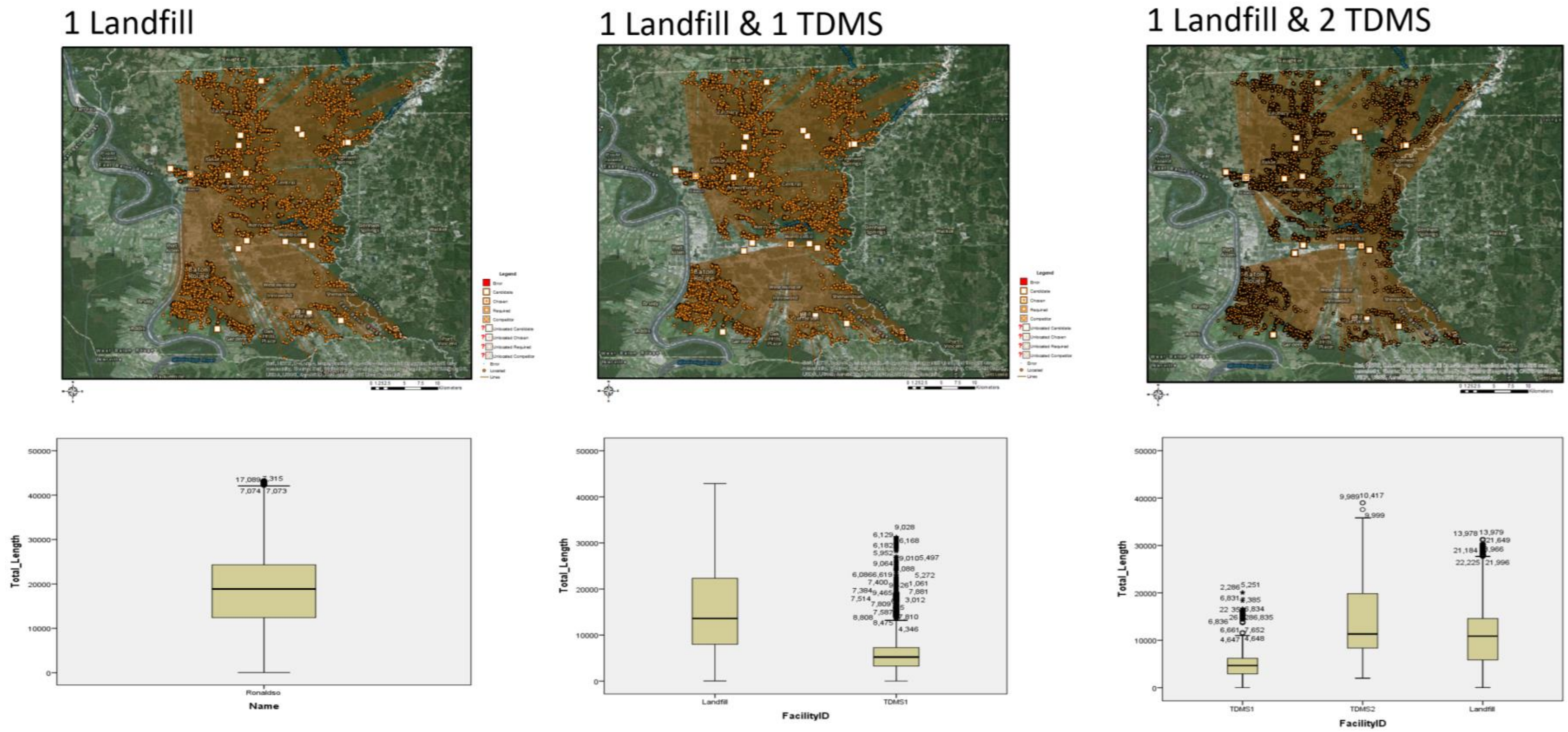


Figure 5-13 Comparison of average distance and SD for the three scenarios.

This research compares the TDMS locations in the City of Baton Rouge with the results of Scenario #3, in which one landfill and two TDMSs are in operation. The City of Baton Rouge opened two TDMS locations (see Figure 5-14):

- TDMS #1: 2876 N. Sherwood Forest Driver, Baton Rouge, LA 70814
- TDMS #2: 6180 Joor Rd, Baton Rouge, LA 70811

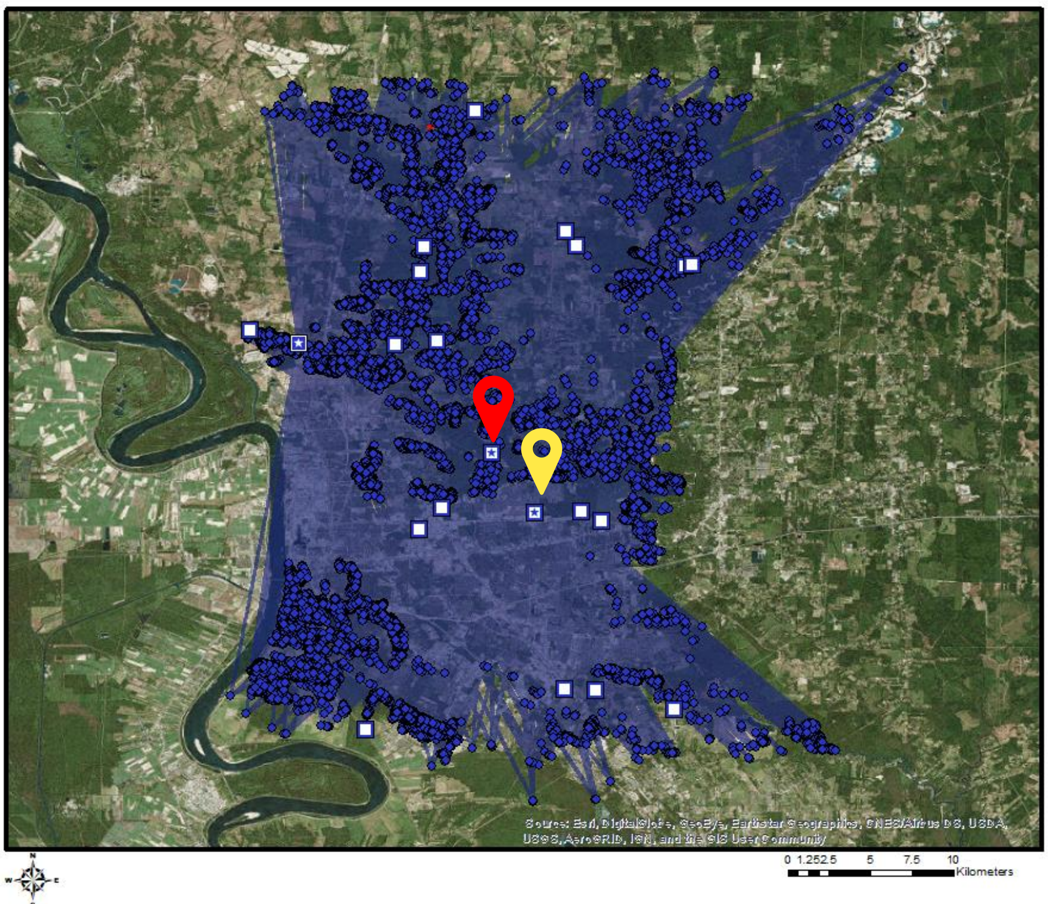


Figure 5-14 TDMS locations in the City of Baton Rouge during the 2016 Louisiana flood
Note: TDMS #1 (yellow marker); TDMS #2 (red marker)

TDMS #2 indicated by the yellow marker was also selected in Scenario #3. TDMS #1, indicated by the red marker, was not selected by Module#3 (TDMS selection and design model) because of its low performance score; the distance from TDMS#1 to water stream (Comite River) of only 0.5km was the reason for the low performance score.

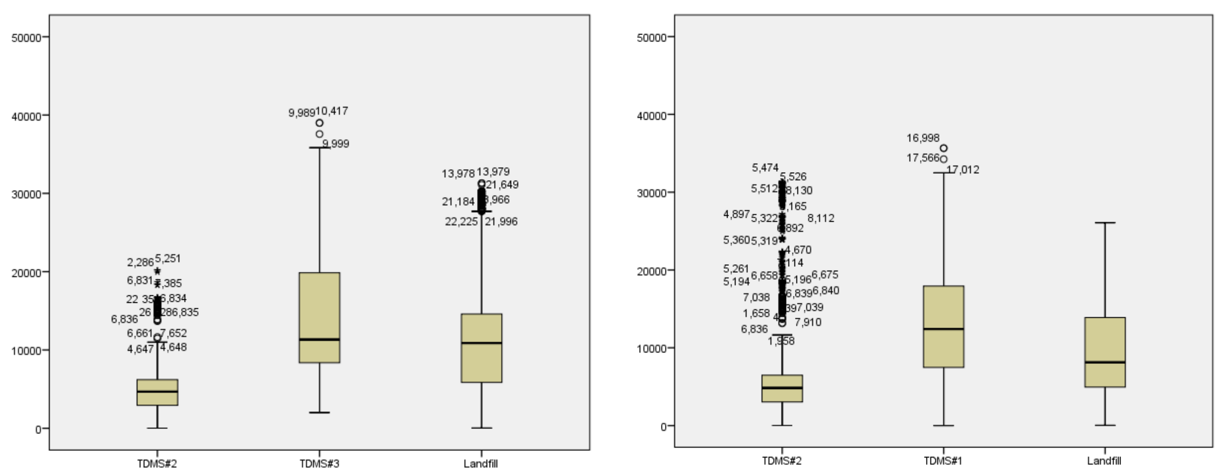
Next, the amount of debris assigned to each TDMSs was considered under the assumption that debris is hauled to the closest facility based on the existing road network (see Table 5-6). In the case of CBR's debris removal practices, more debris was assigned to TDMSs than in Scenario #3.

Table 5-6 Comparison of debris assigned to each facility

Facility	Scenario #3	CBR*	Note
Ronaldson Field landfill**	8,637	6,387	
TDMS #1	-	7,250	Red marker in Figure 5-14
TDMS #2	8,282	8,652	Yellow marker in Figure 5-14
TDMS #3	5,370	-	

**CBR = City of Baton Rouge*
*** The amount of debris assigned to the Ronaldson Field landfill includes only the debris directly hauled to the landfill.*

The average distances and SDs are outlined in Figure 5-15. In the case of the City of Baton Rouge, there are multiple outliers for TDMS #2. This could cause unstable debris input to TDMS #2 due to the variance of the distances from on-site debris to the TDMS (Kim et al. 2018b).



Scenario #3 CBR

Figure 5-15 Comparison of travel distance to each facility

5.4.2 Debris management system behavior and optimization

The user interface (UI) for simulation and analysis is described in Figure 5-16. The UI enables a user to examine agents' behaviors, including hauling trucks, TDMSs, and landfills over time. For example, the number of trucks waiting to unload/load debris at curbside, TDMSs, and landfills. On the right side, the truck utilization rate and the amount of debris in TDMSs and landfills over time are visualized. In Figure 5-16, #1 shows the utilization rate of small and large capacity trucks; #2 describes the amount of debris on curbside (pickup locations), TDMSs, and landfills; #3 and #4 indicate the total amount of debris in TDMSs and landfills over time; and #5 and #6 indicate the average waiting time at curbside and TDMSs.

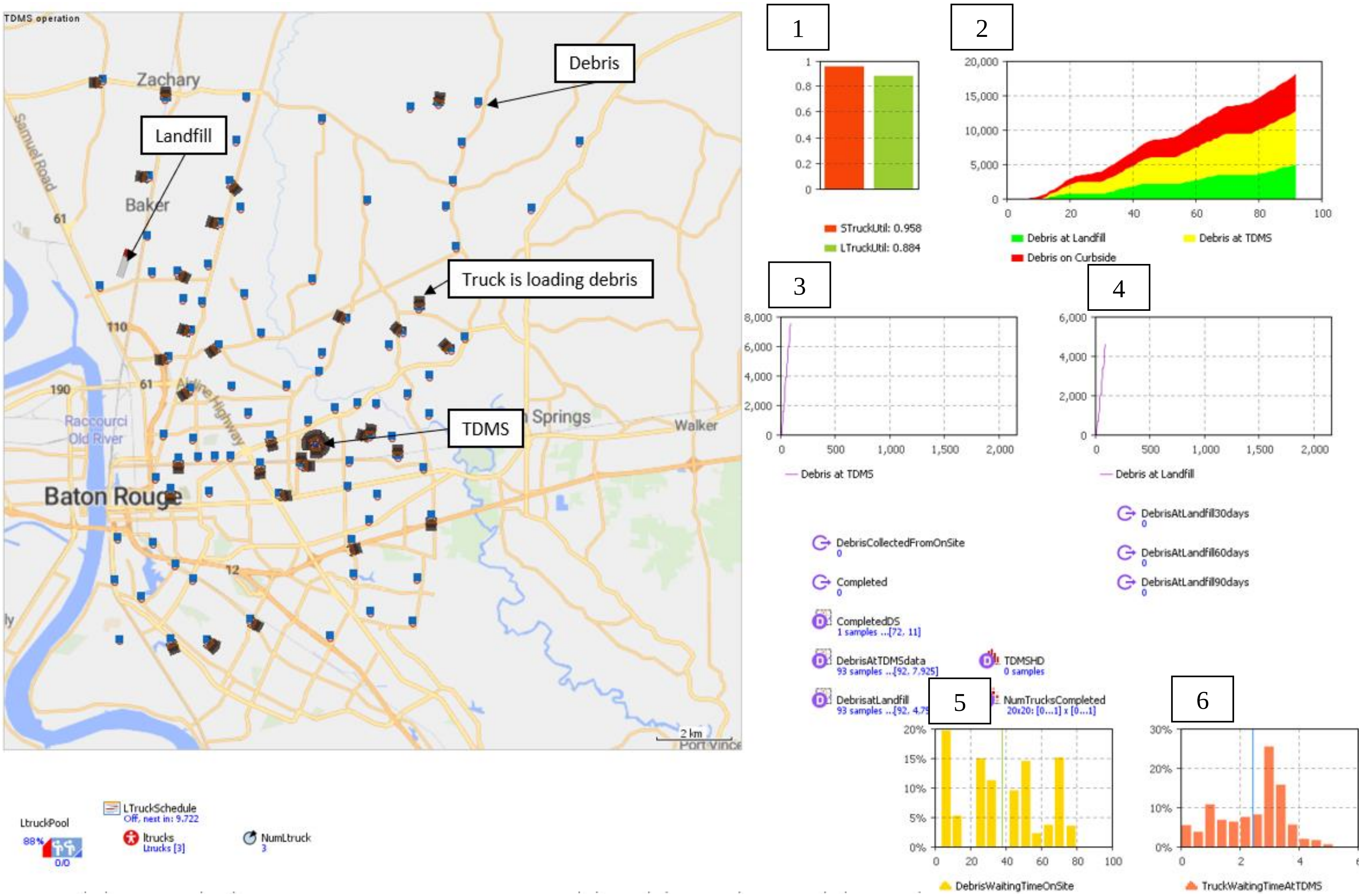


Figure 5-16 User interface of the agent-based model for simulation and analysis

Based on the input parameters in Table 5-5, a simulation experiment (the number of iterations: 500) was conducted to find optimal parameters to maximize truck utilization rates. For the objective function of the optimization, this study denoted, $x_{i,j}^{truck}$, as truck utilization rate - truck type i (25 and 50 CY) and truck ID j . The objective function used in this study is described below (details of optimization functions, parameters and constrains were discussed in depth in Chapter 4).

$$Maximize\ z = \sum_{j \in J} \sum_{i \in I} x_{i,j}^{truck} \quad \forall i \in I, \forall j \in J$$

The objective function was coded using Java below:

```
root.tDMS.trucks.utilization() + root.LtruckPool.utilization()
```

A graphical user interface (GUI) for the optimization process and results is shown in Figure 5-17. The two columns on the left side show the current and best parameters. The current column shows input parameters used for a current simulation experiment (i.e., values for each iteration), and the best column shows the optimal parameters to maximize the truck utilization rate, which is the objective of the study: It found out the optimal parameters (250, 5,4,2) at the 435th iteration (that is the parameters resulting in the maximum utilization rates of small and large trucks out of 500 simulation experiments).

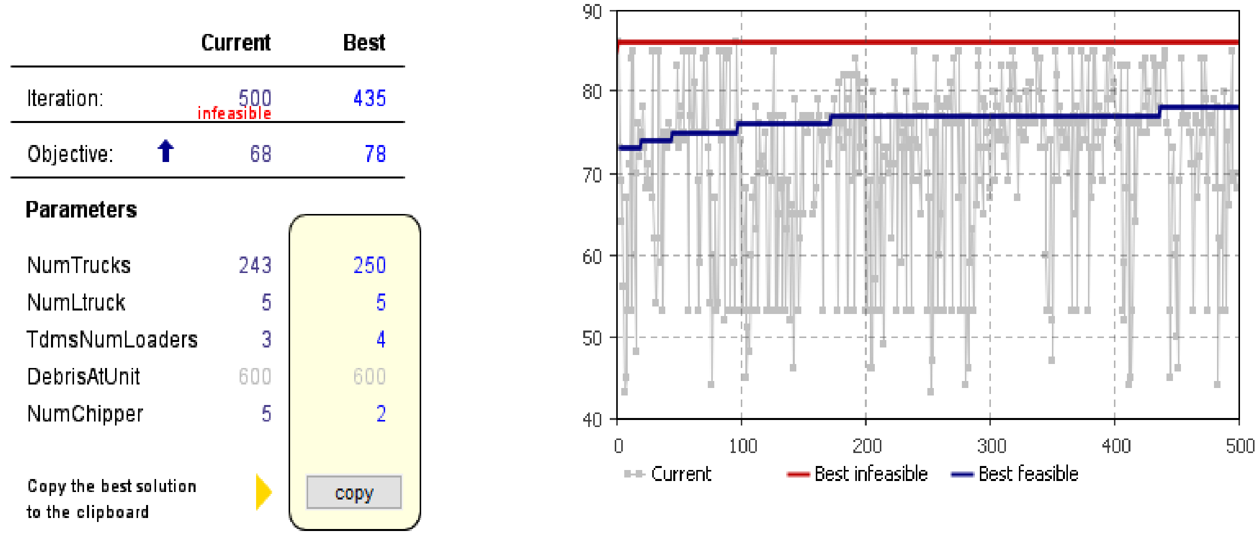


Figure 5-17 Results of system optimization

Note: On the right side, there are three types of lines: grey, blue and red lines. The grey line represents the value of objective function's outcome. The red line represents the best value, but it does not meet the constraints and requirements before/after a simulation. The blue line represents the best outcome that meets all requirement and constraints.

Table 5-7 summarizes the optimal parameters to maximize the objective function (maximum truck utilization rates during debris removal). The required number of large trucks were very smaller than small trucks, 5 vs. 250. There were several reasons behind it. Firstly, the volume of debris was reduced up to 50-75% by chippers or grinders in TDMSs. Secondly, the capacity of large trucks is twice as large as that of small trucks (50 vs. 25 CY). Lastly, travel distance from the TDMSs to the landfill is a fixed distance (11 miles, or 17.7 km), compared to varying distances from debris pickup locations to TDMSs (this caused longer waiting time for unloading at certain moments in TDMS).

Table 5-7 Optimal parameters to maximize truck utilization rates

Parameters	Value
Number of Small Trucks (Cap: 25CY)	250
Number of Large Trucks (Cap. 50CY)	5
Number of Loaders at TDMS	4
Number of Chippers/Grinders at TDMS	2
Amount of debris on at each curbside	600

A sensitivity analysis was conducted to examine impacts of the uncertainty of parameters and environment on the behaviors of debris management system. The input parameters in the sensitivity analysis determined based on the literature in Section 5-2 are described in Table 5-8.

Table 5-8 Input parameters for the sensitivity analysis

Parameter	**Type**	**Value**		
		Min	**Max**	**Step***
Number of small trucks (25CY)	Range	160	200	10
Number of large trucks (50CY)	Range	2	4	2
Loaders at TDMS	Range	2	4	1
Number of chippers at TDMS	Range	1	6	1
Debris at each location	Range	100	300	100

**Step value refers to an added value on exiting parameter values for a next simulation experiment. For example, if the number of small trucks is 160 at the first simulation experiment, the number of small trucks at the next round is 170 (=160+10). While a small value of step provides very detail results of sensitivity analysis, it requires a tremendous amount of computational time. The computational time will be exponentially increased by the number of parameters and step sizes.*

The results are described in Figure 5-18. The amount of debris in a TDMS can range from 150,000 to 450,000 CY. The completion rate for debris removal within 90 days is 80 ~ 100%. A continuous line on (a)~(c) represents the amount of debris in TDMS over time and the line color represents the number of small trucks at each simulation experiment. The blue line shows the experiment results when the number of small trucks is 160 and the red line shows experiment results when the number of small trucks is 200. X-axis on (a)~(c) refers to simulation experiment timestep (1 timestep represents 1 hour). Y-axis on (a)~(b) refers to the amount of debris, and the percentage of debris clean up on (c) respectively. Figures on (d)~(f) refer to the total amount of debris at operation day# 30, 60 and 90 in a landfill. The sensitivity analysis supports to identify the expected amount of debris in a landfill by different operational strategies. x-axis on (d)-(f) refers to the number of small trucks for each simulation experiment and y-axis refers to the amount of debris in a landfill.

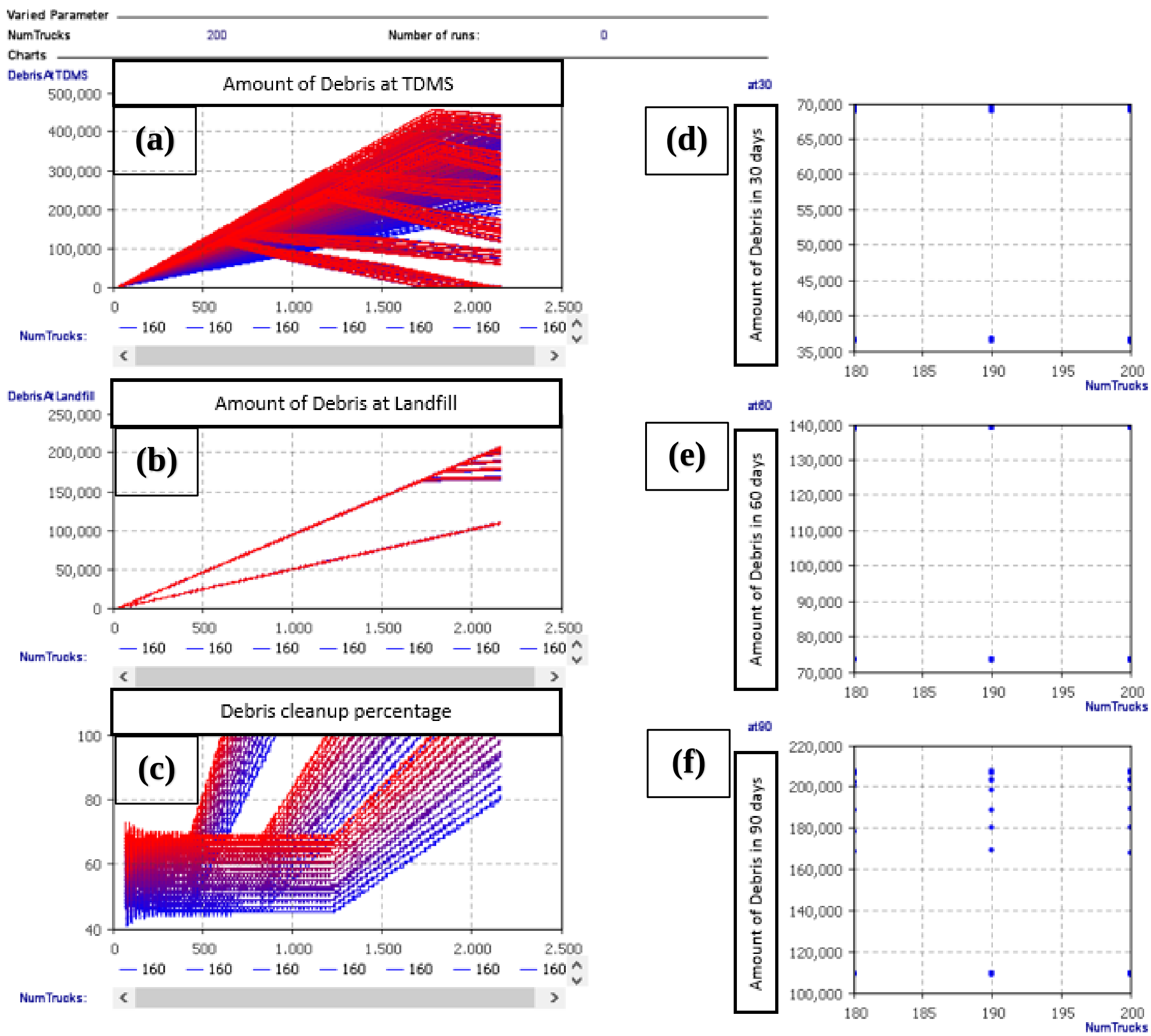


Figure 5-18 Results of sensitivity analysis

5.5 Discussion

In this research, the effectiveness of an adaptive decision support system for debris management was demonstrated in terms of siting TDMSs and simulating debris removal operations in multiple scenarios and optimization. The TDMS design and selection model identified two optimal TDMS candidates; one location is the same as the actual TDMS location, and the other location is close to the actual location of a TDMS in operation after the 2016 Louisiana flood.

In the simulation, this study considered critical parameters, including the number of trucks, loaders, and chippers and amount of debris at each location for effective disaster debris management. The objective function was designed to maximize truck utilization rates during debris removal. The sensitivity analysis identified the importance of a balance between parameters. For example, for the same number of small trucks (190), the amount of collected debris in a TDMS varied from 115,000 to 210,000 CY. Thus, emergency agencies should use a database to examine available resources, so that they can find the optimal combination to maximize performance during an emergency.

Despite these findings, there are several limitations on this study. The following describes the limitations of this study and areas for future research:

Uncertainty of debris estimation: Debris estimation is the basic foundation of the process of optimizing a debris management system as it determines the required capacity of facilities as well as the required resources. While there are several models to estimate the amount of debris by USACE and FEMA, the error of margin is almost always 10% or more (Escobedo et al. 2009). In multiple after-action reports, many agencies indicated that the unexpected amount of debris generated hampered the entire debris removal process. Thus, it is necessary to develop new methodologies to estimate the amount of debris generated, such as real-time data collection using UAVs and image processing for estimating the volume and type of debris located curbside, as well as smartphone-based user input. These methods will help decision makers obtain up-to-date information and data related to the amount of debris in a community and examine the effectiveness of existing debris removal operation systems over time.

Near real-time information and data related to the road network: The travel time of hauling trucks significantly affects the overall debris removal time. This research is limited because it applies only the average speed of trucks (between 40 and 55 miles per hour) for each truck agent. However, travel times may differ during rush hour. Thus, there is a need to develop a method for strategic real-time resource routing and allocation based on road condition or traffic status during disaster recovery. It enables to reduce the overall idle time of trucks and maximize utilization rates during debris removal operation.

TDMS design and layout: Another limitation of this study is its limited focus on TDMS location and the optimal number of resources for a TDMS. In addition, the type of debris was limited to recyclable and non-recyclable materials. In the real world, the debris would be more complex and include numerous types such as hazardous materials, mixed debris, and other materials requiring chemical or biological treatment by special equipment and trained staff. Thus, further studies are required to design a TDMS layout that maximizes the utilization of space based on the type of debris and need for specialized equipment. By integrating these considerations into the adaptive decision support system, emergency agencies will have a better decision tool for effective debris management.

5.6 Conclusion

This study applied the adaptive decision support system to a case study, namely debris removal in the City of Baton Rouge after the 2016 Louisiana flood, to examine system performance in terms of TDMS locations and system optimization. A sensitivity analysis was also conducted. The comprehensive literature related to debris removal practices in the City of Baton Rouge identified the main issues and problems during debris removal, including a lack of capacity and resources, the installation of TDMSs to increase debris handling capacity, and unclear regulation for certain types of debris. Based on the information and data collected, this study included the following: 1) identification of TDMSs, 2) system optimization to maximize resource utilization rates (trucks), and 3) sensitivity analysis to examine the uncertainty of input parameters such as the number of available trucks, chippers, and loaders and the amount of debris generated.

The adaptive decision support system developed by the GIS- and agent-based model would enable decision makers to: 1) examine existing debris management system performance under multiple uncertainties after a catastrophic event and 2) include the impacts of a disaster on a community into the adaptive decision support system to re-examine debris removal system performance under certain scenarios. In addition, the developed GUI of the system reflected the information and data required by decision makers in terms of the amount of debris in TDMSs and landfills over time, resource utilization rates (trucks), completion of debris removal in 30, 60, and 80 days, and trucks' waiting time to unload debris. Lastly, each component in the system is designed as a single module (agent). Other modules can be easily integrated into the system, such as material recycling systems, layout and design of TDMS systems, and real-time traffic information.

CHAPTER 6. SUMMARY AND CONCLUSION

6.1 Research summary

Debris management is a critical component of successful disaster management. While there are numerous disaster mitigation strategies and post-disaster debris management plans, they are often difficult to implement because of the complexity of debris management during a disaster, including (i) the uniqueness of disaster incidents and randomness of its impacts; (ii) the complexity of disaster debris removal operations, policy, and regulations; and (iii) system interdependency of multiple infrastructure networks.

This study systematically summarized cutting-edge knowledge about debris management processes and related policies and regulations to handle debris generated by flooding. While many studies have explored multi-faceted post-disaster management and its complexities, there are few that have developed a model that adopts a system-of-systems approach to capture the complexity and dynamics of debris removal operations after a disaster. Further, the existing body of literature lacks a set of theories and an organized framework, which will be critical for researchers, agencies, and practitioners in the field of post-disaster management. This study also reviewed three simulation methods for modeling complex systems, namely discrete events, system dynamics, and agent-based modeling. Finally, there is a need to increase the transparency of decision making, especially with respect to compromises between engineering and technical efficiency and social and political realities of a particular context. Traditional methods of risk assessment that analyze the dynamics of a context do not facilitate the integration of the behavior of different actors within the decision context.

Based on the broad literature review, this research proposed a framework for effective disaster debris management. Within the framework, four modules were designed to systemize each process as well integrate sub-systems into the framework. Module #1 is a geo-database to store critical GIS data such as that on road networks and waste-related facilities as well as community-related data. Module #2 is designed to understand the community structure using network analysis. It enables gaining knowledge of the community structure and prioritizing debris removal works. In

Module #3, TDMS selection and design model are determined to identify TDMS candidates and optimal locations using information and data from Modules #1 and 2. Module #4 involves agent-based modeling to analyze system behavior and dynamics under multiple disaster impact and debris removal scenarios. Hauling trucks and waste-related facilities are represented as agents, and data and information from Modules #1 to 3 are used to build an environment for the agents.

This research conducted a case study to test and validate the outcome of the adaptive decision support system. Data related to debris removal in the City of Baton Rouge after the 2016 Louisiana flood was collected from news, reports, and the City of Baton Rouge. The TDMS candidates identified during this research were used in the City of Baton Rouge for handling debris generated. With the same amount of equipment (trucks), the estimated debris removal time was very close to the actual time. A sensitivity analysis was also conducted to enhance model validity; this was based on the impact of the number of trucks to haul debris to the TDMS and/or landfill over time. The research provided optimal solutions to maximize debris removal performance under certain constraints in terms of equipment utilization levels and TDMS and landfill capacities.

To sum up, this study applied a system-of-systems approach to develop an adaptive decision support system to understand the behaviors and dynamics of a complex disaster debris management system as well as optimize the system's efficiency under certain constraints during disaster recovery. The proposed adaptive decision support system will be beneficial for emergency agencies and disaster-prone communities to evaluate existing disaster debris management plans as well as maximize system performance under certain disaster scenarios. Further, the transparency of the decision-making process for TDMSs under technical, environmental, and social perspectives will help communities minimize opposition to building TDMSs near their areas, such as a NIMBY approach.

6.2 Research contributions to the body of knowledge and practices

In the presence of the identified gap in the existing literature related to debris management, this research aimed to develop an adaptive system-of-systems model for the analysis of complex debris management systems to understand the inherent and emergent dynamics and associated complexities. Further, the decision support system was aimed at navigating debris removal efficiency through modeling, simulation, and visualization of the process. The decision is modeled at the interface of the infrastructure network and community preferences. Research contributions to the study include:

i. Complex systems modeling using spatial agent-based modeling: This research developed spatial agent-based modeling to understand a complex disaster debris management system. This will enable decision makers to simulate the complex systems based on designed parameters and constraints. The simulation results, optimization, and sensitivity analysis will support their understanding of system behaviors over time and enable effective decision making on critical components of debris management.

ii. Integrating analysis of technical, environmental, and social dynamics into the engineering assessment of post-disaster management: This holistic approach will add to the depth of the solution and contribute to a systemic understanding of the emergent dynamics. The debris removal process is modeled at the interface of community and the infrastructure network, while the TDMS network, as the core of the process, is designed as a multi-layer model to facilitate the integration of institutional arrangements into strategy development and policy making. These arrangements can be integrated through institutional resources and mechanisms in the form of penalties, rewards, or a change of utility for each actor. Institutional elements can be regarded as a significant resource for any actor as part of the interplay of the actors. The proposed method provides a quantified-descriptive approach for communities to choose alternative resources or mechanisms as a modification for strategies and policies to promote socially sustainable alternatives or prevent socially unacceptable alternatives.

iii. Increasing the transparency of decision making, specifically with respect to compromise between engineering and technical efficiency for the social and environmental reality of the context: Traditional methods of risk assessment in post-disaster management 1) lack a combined quantitative and descriptive approach to include and analyze the dynamics of a context and 2) do not facilitate integrations of the behaviors of different actors/parties within the decision context. This study attempted to reduce this gap through a multi-layer decision model for selecting a TDMS network that considers both technical, environmental and social aspects. Planners can apply the proposed framework to explore compromises between different layers and increase the transparency of decisions in diverse settings, for example, the general case of social embeddedness of infrastructure or public displacement. This is further enhanced through the visualization of the platform.

iv. A systemic approach to the context that involve multiple decision makers: A potential misconception for decision makers in the public policy domain is to suppose that consequences are solely determined by their decisions. This misconception often results in optimism bias and negligence of the costs accompanying the emergent risks associated with interactional dynamics. The proposed framework can facilitate a causal explanation of lock-ins within the network and provide a foundation for the development of innovative policies and strategies**.**

v. Increasing the understanding of emergency operations at the nexus of the community, infrastructure, and the environment: Interactional elements cover broad concepts that can be added to policy making, such as economic, environmental, social-political-institutional, as well as engineering-technical aspects. Integrating all factors within one framework along with a real-time simulation of the process will help planners to develop strategies at the nexus of the communities, infrastructure, and the environment while they uncover emergent dynamics. The proposed model aims to reflect the complexity of this nexus within the model and its simulation.

vi. Facilitating communication of different agencies to increase the chance of collaborative behavior: Visualization is an alternative communication channel for plans, policies, and strategies among different agencies. These agencies, with their specific agendas, can discuss and share their (sometimes contrasting) ideas about different layers of decision with clear variables. Furthermore, communication can be supported and validated by real-time simulation, including unexpected bottlenecks during post-disaster debris management operations.

6.3 Limitations of this research and recommendations for future research

The proposed adaptive decision support system for effective disaster debris management has several limitations in terms of debris estimation, debris removal performance prediction, and system interdependency. The following describes the existing limitations of this research:

i. **Debris estimation methods**: Hazus-MH is broadly used as a risk assessment simulation tool, including for disaster debris estimation under multiple types of disaster scenarios. Existing state- and local-level disaster mitigation strategies and post-disaster debris management operations significantly depend on simulation results by Hazus-MH. Thus, the validation and verification of disaster debris estimation by Hazus-MH are critical to maximizing system efficiency of post-disaster debris removal operations. A typical term of validation refers to the comparison of model outputs with observed or collected data. While the majority of emergency agencies are aware of the importance of effective disaster debris removal, there are few after-action reports or data that reveal details of disaster debris removal operations during disasters. Thus, small-scale data collection through interviews and questionnaires is required to validate existing debris removal estimation systems and calibrate existing debris management systems. Further, rapid debris estimation methods using images and videos as well as crowd-sourced data are needed to estimate precisely the amount of debris after a disaster. Finally, national-, state-, and local-level databases should be developed to share detailed data for further system analysis.

ii. **Strategies for diverse types of disaster debris**: The types of debris estimated by Hazus-MH are limited to building debris (steel, masonry, wood, and concrete) and tree debris. It is difficult to estimate recyclable or hazardous waste from residential and industrial areas. For example, tremendous recyclable waste was generated during the Flint, Michigan water crisis (Wang et al. 2019). However, the city and waste-related companies did not have sufficient facilities or equipment to handle it. Most were unable to track or transport the waste to landfills using an appropriate process. Further, most of the after-action reports after disasters focused on sharing the overall amount of debris generated and the cost to handle it. They did not include information on sustainable approaches to handling recyclable or hazardous waste during the recovery period. Thus, further research is necessary to review historical recyclable/hazardous debris treatment and develop appropriate regulations and policies. A field study will be beneficial to examine specific types of debris generated from residential and industrial areas.

iii. **System interdependency and uncertainty**: This study was limited to integrated sub-systems for disaster debris management, such as waste-related facilities, TDMSs, the road network, and the built environment to improve the performance and prediction of debris removal operations. While debris management is a critical component for effective disaster management, it is also a sub-system of any disaster management system. That is, the success of debris removal may improve disaster management system performance but cannot guarantee post-disaster recovery success. For example, operating a certain number of hauling trucks can trigger heavy traffic in a disaster-affected community, which could hamper other emergency medical and supply systems. Thus, integration of debris management into the disaster management system is necessary to improve overall management quality as well as develop better post-disaster recovery strategies.

iv. **System uncertainty and methods**: The adaptive decision support system (DSS) can be employed in either pre- and post-disaster situations. In a pre-disaster situation, the adaptive DSS can retrieve data and information from Hazus-MH (e.g. disaster-impact prediction and debris estimation), historical infrastructure damages, and pre-determined TDMSs from state- and local disaster mitigation planning books. However, multiple input data used in the adaptive DSS would have certain level of uncertainty and variability with respect to the actual situations. Thus, there is a need for accounting for risks (coming from the uncertainties in system components) in the quantitative analysis and decision-making in the adaptive decision support system. Stochastic modeling and Monte Carlo simulation (method) will be a future research direction to provide all the possible outcomes from coming decision-making and the impacts of risk. It allows better decision-making under uncertainty of disaster impacts as well as debris management systems for disaster mitigation planning. In a post-disaster situation, GIS database in Module#1 enables the adaptive DSS to store/retrieve up-to-date data and information as available (e.g., road network status, amount of debris on a curbside). By employing lower level of uncertainty in data and information, the overall performance and prediction from the adaptive DSS will be enhanced.

v. **Spatial and temporal scale of a simulation model**: The proposed simulation model was developed using agent-based modeling. As described in Section 2.3, agent-based modeling is an increasingly popular method for analyzing, visualizing, and understanding system behaviors and dynamics in complex systems. In a city-level case study, simulating the proposed models, including single- and multi-objective optimizations and a sensitivity analysis, took 60 ~ 500 minutes. However, there are several limitations to large-scale simulation in terms of the huge computational power requirement compared to analytical methods as well as the possible lack of GIS-related data required for such a simulation. Thus, further research is required to identify specific needs of national-, state-, and local-level agencies. This will provide guidelines to develop tailored simulation models and data pipelines to deliver well-systematized information and results for higher- and lower-level systems.

vi. **Database**: Numerous emergency agencies recognize the crucial role of disaster-related data and information to develop disaster mitigation strategies as well as post-disaster debris removal operations. For example, many scholars use data from EMDAT, the International disaster database, to examine patterns and characteristics of disaster impacts. However, there is no agreed-upon database platform to store and share historical information and data on debris removal operations and strategies. Developing a database related to debris removal is essential for sharing critical information, technologies, and know-how between researchers, agencies, and organizations. This will allow emergency agencies, policymakers, and researchers to develop better disaster planning for preparedness, responses, and recovery.

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APPENDIX A. DESCRIPTION OF INPUT DATA ON GEOPROCESSING

Model Report	Expand/Collapse All

Generated on: Wed Apr 04 20:33:34 2018

Variables

WETLAND

*Data Type:*Feature Layer
*Value:*Environment\WETLAND

RegionDEM_area

*Data Type:*Raster Layer
*Value:*RegionDEM_area

Output direction raster

*Data Type:*Raster Dataset
Value:

EF:hzSchool

*Data Type:*Feature Layer
*Value:*Utilities\EF:hzSchool

Output direction raster (2)

*Data Type:*Raster Dataset
Value:

EF:hzEmergencyCtr

*Data Type:*Feature Layer
*Value:*Utilities\EF:hzEmergencyCtr

Output direction raster (3)

*Data Type:*Raster Dataset
Value:

EF:hzCareFlty

*Data Type:*Feature Layer
*Value:*Utilities\EF:hzCareFlty

Output direction raster (4)

*Data Type:*Raster Dataset
Value:

airport

*Data Type:*Feature Layer
*Value:*Infrastructure\airport

Output direction raster (5)

*Data Type:*Raster Dataset
Value:

historiclocations

*Data Type:*Feature Layer
*Value:*historiclocations

Output direction raster (6)

*Data Type:*Raster Dataset
Value:

Reaches

*Data Type:*Feature Layer
*Value:*Reaches

Output direction raster (7)

*Data Type:*Raster Dataset
Value:

mainroads

*Data Type:*Feature Layer
*Value:*Infrastructure\mainroads

Output direction raster (8)

*Data Type:*Raster Dataset
Value:

selectedresidential

*Data Type:*Feature Layer
*Value:*selectedresidential

Output direction raster (9)

*Data Type:*Raster Dataset
Value:

UNDareas

*Data Type:*Feature Layer
*Value:*UNDareas

Output direction raster (10)

*Data Type:*Raster Dataset
Value:

100 year floodplan

*Data Type:*Feature Layer
*Value:*Floodlayers\100 year floodplan

Output direction raster (11)

*Data Type:*Raster Dataset
Value:

Extract_Slop1

*Data Type:*Raster Layer
*Value:*Extract_Slop1

Reclass_slope

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_slope

EucDist_wetland

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_wetland

Extract_wetland

*Data Type:*Raster Dataset
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Reclass_wetland

*Data Type:*Raster Dataset
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EucDist_School

*Data Type:*Raster Dataset
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Extract_school

*Data Type:*Raster Dataset
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Reclass_school

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_school

EucDist_EmergencyCtr

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_EmergencyCtr

Extract_emergencycare

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_emergencycare

Reclass_emergencycare

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_emergencycare

EucDist_hzCareFlty

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_hzCareFlty

Extract_hzCareFlty

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_hzCareFlty

Reclass_hzCareFlty

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_hzCareFlty

EucDist_airport

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_airport

Extract_airport

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_airport

Reclass_airport

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_airport

EucDist_historicplaces

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_historicplaces

Extract_historicplaces

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_historicplaces

Reclass_historicplaces

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_historicplaces

EucDist_UNDareas

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_UNDareas

Extract_UNDareas

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_UNDareas

Reclass_UNDareas

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_UNDareas

EucDist_floodplan

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_floodplan

Extract_floodplan

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_floodplan

Reclass_floodplan

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_floodplan

EucDist_reaches

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_reaches

Extract_reaches

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_reaches

Reclass_reaches

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_reaches

Weighte_Recl1

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Weighte_Recl1

EucDist_residential

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_residential

Extract_residential

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_residential

FuzzyMe_residential

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\FuzzyMe_residential

EucDist_mainroads

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_mainroads

Extract_roads

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_roads

FuzzyMe_mainroad

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\FuzzyMe_mainroad

TDMSlocations

*Data Type:*Raster Dataset
*Value:*C:\Users\jooho\Google Drive\GISdata\BR.gdb\TDMSlocations

Processes

Euclidean Distance

*Tool Name:*Euclidean Distance
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Distance\EucDistance

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster or feature source data	Input	Required	Composite Geodataset	Environment\WETLAND
Output distance raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_wetland
Maximum distance	Input	Optional	Double	
Output cell size	Input	Optional	Analysis Cell Size	183.446565810442
Output direction raster	Output	Optional	Raster Dataset	

Messages:

Executing (Euclidean Distance): EucDistance Environment\WETLAND "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_wetland" # 183.446565810442 #

Start Time: Tue Jul 11 17:22:28 2017

Succeeded at Tue Jul 11 17:22:29 2017 (Elapsed Time: 1.23 seconds)

Euclidean Distance (2)

*Tool Name:*Euclidean Distance
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Distance\EucDistance

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster or feature source data	Input	Required	Composite Geodataset	Utilities\EF:hzSchool
Output distance raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_School
Maximum distance	Input	Optional	Double	
Output cell size	Input	Optional	Analysis Cell Size	183.446565810442
Output direction raster	Output	Optional	Raster Dataset	

Messages:

Executing (Euclidean Distance (2)): EucDistance Utilities\EF:hzSchool "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_School" # 183.446565810442 #

Start Time: Tue Jul 11 17:22:29 2017

Succeeded at Tue Jul 11 17:22:30 2017 (Elapsed Time: 0.88 seconds)

Euclidean Distance (3)

*Tool Name:*Euclidean Distance
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Distance\EucDistance

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster or feature source data	Input	Required	Composite Geodataset	Utilities\EF:hzEmergencyCtr
Output distance raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_EmergencyCtr
Maximum distance	Input	Optional	Double	
Output cell size	Input	Optional	Analysis Cell Size	183.446565810442
Output direction raster	Output	Optional	Raster Dataset	

Messages:

Executing (Euclidean Distance (3)): EucDistance Utilities\EF:hzEmergencyCtr "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_EmergencyCtr" # 183.446565810442 #

Start Time: Tue Jul 11 17:22:30 2017

Succeeded at Tue Jul 11 17:22:31 2017 (Elapsed Time: 0.63 seconds)

Euclidean Distance (4)

*Tool Name:*Euclidean Distance
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Distance\EucDistance

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster or feature source data	Input	Required	Composite Geodataset	Utilities\EF:hzCareFlty
Output distance raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_hzCareFlty
Maximum distance	Input	Optional	Double	
Output cell size	Input	Optional	Analysis Cell Size	183.446565810442
Output direction raster	Output	Optional	Raster Dataset	

Messages:

Executing (Euclidean Distance (4)): EucDistance Utilities\EF:hzCareFlty "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_hzCareFlty" # 183.446565810442 #

Start Time: Tue Jul 11 17:22:31 2017

Succeeded at Tue Jul 11 17:22:32 2017 (Elapsed Time: 0.61 seconds)

Euclidean Distance (5)

*Tool Name:*Euclidean Distance
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Distance\EucDistance

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster or feature source data	Input	Required	Composite Geodataset	Infrastructure\airport
Output distance raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_airport
Maximum distance	Input	Optional	Double	
Output cell size	Input	Optional	Analysis Cell Size	183.446565810442
Output direction raster	Output	Optional	Raster Dataset	

Messages:

- Executing (Euclidean Distance (5)): EucDistance Infrastructure\airport "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_airport" # 183.446565810442 #
- Start Time: Tue Jul 11 17:22:32 2017
- Succeeded at Tue Jul 11 17:22:32 2017 (Elapsed Time: 0.61 seconds)

Euclidean Distance (6)

*Tool Name:*Euclidean Distance
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Distance\EucDistance

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster or feature source data	Input	Required	Composite Geodataset	historiclocations
Output distance raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_historicplaces
Maximum distance	Input	Optional	Double	
Output cell size	Input	Optional	Analysis Cell Size	183.446565810442
Output direction raster	Output	Optional	Raster Dataset	

Messages:

- Executing (Euclidean Distance (6)): EucDistance historiclocations "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_historicplaces" # 183.446565810442 #
- Start Time: Tue Jul 11 17:22:33 2017
- Succeeded at Tue Jul 11 17:22:33 2017 (Elapsed Time: 0.66 seconds)

Euclidean Distance (7)

*Tool Name:*Euclidean Distance
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Distance\EucDistance

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster or feature source data	Input	Required	Composite Geodataset	Reaches
Output distance raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_reaches
Maximum distance	Input	Optional	Double	
Output cell size	Input	Optional	Analysis Cell	183.446565810442

			Size	
Output direction raster	Output	Optional	Raster Dataset	

Messages:

- Executing (Euclidean Distance (7)): EucDistance Reaches "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_reaches" # 183.446565810442 #
- Start Time: Tue Jul 11 17:22:33 2017
- Succeeded at Tue Jul 11 17:22:34 2017 (Elapsed Time: 0.63 seconds)

Euclidean Distance (8)

*Tool Name:*Euclidean Distance
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Distance\EucDistance

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster or feature source data	Input	Required	Composite Geodataset	Infrastructure\mainroads
Output distance raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_mainroads
Maximum distance	Input	Optional	Double	
Output cell size	Input	Optional	Analysis Cell Size	183.446565810442
Output direction raster	Output	Optional	Raster Dataset	

Messages:

- Executing (Euclidean Distance (8)): EucDistance Infrastructure\mainroads "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_mainroads" # 183.446565810442 #
- Start Time: Tue Jul 11 17:22:34 2017
- Succeeded at Tue Jul 11 17:22:35 2017 (Elapsed Time: 0.66 seconds)

Euclidean Distance (9)

*Tool Name:*Euclidean Distance
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Distance\EucDistance

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster or feature source data	Input	Required	Composite Geodataset	selectedresidential
Output distance raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_residential

Maximum distance	Input	Optional	Double	
Output cell size	Input	Optional	Analysis Cell Size	183.446565810442
Output direction raster	Output	Optional	Raster Dataset	

Messages:

- Executing (Euclidean Distance (9)): EucDistance selectedresidential "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_residential" # 183.446565810442 #
- Start Time: Tue Jul 11 17:22:35 2017
- Succeeded at Tue Jul 11 17:22:42 2017 (Elapsed Time: 6.96 seconds)

Euclidean Distance (10)

*Tool Name:*Euclidean Distance
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Distance\EucDistance

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster or feature source data	Input	Required	Composite Geodataset	UNDareas
Output distance raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_UNDareas
Maximum distance	Input	Optional	Double	
Output cell size	Input	Optional	Analysis Cell Size	183.446565810442
Output direction raster	Output	Optional	Raster Dataset	

Messages:

- Executing (Euclidean Distance (10)): EucDistance UNDareas "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_UNDareas" # 183.446565810442 #
- Start Time: Tue Jul 11 17:22:42 2017
- Succeeded at Tue Jul 11 17:22:44 2017 (Elapsed Time: 2.40 seconds)

Euclidean Distance (11)

*Tool Name:*Euclidean Distance
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Distance\EucDistance

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster or feature source data	Input	Required	Composite Geodataset	Floodlayers\100 year floodplan

Output distance raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_floodplan
Maximum distance	Input	Optional	Double	
Output cell size	Input	Optional	Analysis Cell Size	183.446565810442
Output direction raster	Output	Optional	Raster Dataset	

Messages:

- Executing (Euclidean Distance (11)): EucDistance "Floodlayers\100 year floodplan" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_floodplan" # 183.446565810442 #
- Start Time: Tue Jul 11 17:22:45 2017
- Succeeded at Tue Jul 11 17:22:55 2017 (Elapsed Time: 10.45 seconds)

Reclassify (7)

*Tool Name:*Reclassify
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Reclass\Reclassify

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	Extract_Slop1
Reclass field	Input	Required	Field	VALUE
Reclassification	Input	Required	Remap	0 10 1;10 100 0
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_slope
Change missing values to NoData	Input	Optional	Boolean	false

Messages:

- Executing (Reclassify (7)): Reclassify Extract_Slop1 VALUE "0 10 1;10 100 0" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_slope" DATA
- Start Time: Tue Jul 11 17:22:55 2017
- Succeeded at Tue Jul 11 17:22:56 2017 (Elapsed Time: 0.68 seconds)

Extract by Mask

*Tool Name:*Extract by Mask
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Extraction\ExtractByMask

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite	C:\Users\jooho\Google

			Geodataset	Drive\GISdata\BR.gdb\EucDist_wetland
Input raster or feature mask data	Input	Required	Composite Geodataset	RegionDEM_area
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_wetland

Messages:

- Executing (Extract by Mask): ExtractByMask "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_wetland" RegionDEM_area "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_wetland"
- Start Time: Tue Jul 11 17:22:56 2017
- Succeeded at Tue Jul 11 17:22:57 2017 (Elapsed Time: 0.55 seconds)

Reclassify

*Tool Name:*Reclassify
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Reclass\Reclassify

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_wetland
Reclass field	Input	Required	Field	VALUE
Reclassification	Input	Required	Remap	0 100 0;100 500000 1
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_wetland
Change missing values to NoData	Input	Optional	Boolean	false

Messages:

- Executing (Reclassify): Reclassify "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_wetland" VALUE "0 100 0;100 500000 1" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_wetland" DATA
- Start Time: Tue Jul 11 17:22:57 2017
- Succeeded at Tue Jul 11 17:22:57 2017 (Elapsed Time: 0.53 seconds)

Extract by Mask (2)

*Tool Name:*Extract by Mask
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Extraction\ExtractByMask

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_School

Input raster or feature mask data	Input	Required	Composite Geodataset	RegionDEM_area
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_school

Messages:

- Executing (Extract by Mask (2)): ExtractByMask "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_School" RegionDEM_area "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_school"
- Start Time: Tue Jul 11 17:22:59 2017
- Succeeded at Tue Jul 11 17:23:00 2017 (Elapsed Time: 0.55 seconds)

Reclassify (2)

*Tool Name:*Reclassify
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Reclass\Reclassify

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_school
Reclass field	Input	Required	Field	VALUE
Reclassification	Input	Required	Remap	0 304.800000 0;304.800000 500000 1
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_school
Change missing values to NoData	Input	Optional	Boolean	false

Messages:

- Executing (Reclassify (2)): Reclassify "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_school" VALUE "0 304.800000 0;304.800000 500000 1" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_school" DATA
- Start Time: Tue Jul 11 17:23:00 2017
- Succeeded at Tue Jul 11 17:23:01 2017 (Elapsed Time: 0.54 seconds)

Extract by Mask (3)

*Tool Name:*Extract by Mask
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Extraction\ExtractByMask

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_EmergencyCtr
Input raster or feature mask data	Input	Required	Composite Geodataset	RegionDEM_area

Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_emergencycare

Messages:

- Executing (Extract by Mask (3)): ExtractByMask "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_EmergencyCtr" RegionDEM_area "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_emergencycare"
- Start Time: Tue Jul 11 17:23:01 2017
- Succeeded at Tue Jul 11 17:23:01 2017 (Elapsed Time: 0.54 seconds)

Reclassify (3)

*Tool Name:*Reclassify
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Reclass\Reclassify

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_emergencycare
Reclass field	Input	Required	Field	VALUE
Reclassification	Input	Required	Remap	0 304.800000 0;304.800000 1600000 1
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_emergencycare
Change missing values to NoData	Input	Optional	Boolean	false

Messages:

- Executing (Reclassify (3)): Reclassify "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_emergencycare" VALUE "0 304.800000 0;304.800000 1600000 1" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_emergencycare" DATA
- Start Time: Tue Jul 11 17:23:01 2017
- Succeeded at Tue Jul 11 17:23:02 2017 (Elapsed Time: 0.52 seconds)

Extract by Mask (4)

*Tool Name:*Extract by Mask
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Extraction\ExtractByMask

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_hzCareFlty
Input raster or feature mask data	Input	Required	Composite Geodataset	RegionDEM_area
Output raster	Output	Required	Raster	C:\Users\jooho\Google

			Dataset	Drive\GISdata\BR.gdb\Extract_hzCareFlty

Messages:

- Executing (Extract by Mask (4)): ExtractByMask "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_hzCareFlty" RegionDEM_area "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_hzCareFlty"
- Start Time: Tue Jul 11 17:23:02 2017
- Succeeded at Tue Jul 11 17:23:03 2017 (Elapsed Time: 0.54 seconds)

Reclassify (4)

*Tool Name:*Reclassify
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Reclass\Reclassify

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_hzCareFlty
Reclass field	Input	Required	Field	VALUE
Reclassification	Input	Required	Remap	0 304.800000 0;304.800000 1600000 1
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_hzCareFlty
Change missing values to NoData	Input	Optional	Boolean	false

Messages:

- Executing (Reclassify (4)): Reclassify "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_hzCareFlty" VALUE "0 304.800000 0;304.800000 1600000 1" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_hzCareFlty" DATA
- Start Time: Tue Jul 11 17:23:03 2017
- Succeeded at Tue Jul 11 17:23:03 2017 (Elapsed Time: 0.52 seconds)

Extract by Mask (5)

*Tool Name:*Extract by Mask
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Extraction\ExtractByMask

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_airport
Input raster or feature mask data	Input	Required	Composite Geodataset	RegionDEM_area
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_airport

Messages:

- Executing (Extract by Mask (5)): ExtractByMask "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_airport" RegionDEM_area "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_airport"
- Start Time: Tue Jul 11 17:23:03 2017
- Succeeded at Tue Jul 11 17:23:04 2017 (Elapsed Time: 0.54 seconds)

Reclassify (5)

*Tool Name:*Reclassify
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Reclass\Reclassify

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_airport
Reclass field	Input	Required	Field	VALUE
Reclassification	Input	Required	Remap	0 3048 0;3048 3600000 1
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_airport
Change missing values to NoData	Input	Optional	Boolean	false

Messages:

- Executing (Reclassify (5)): Reclassify "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_airport" VALUE "0 3048 0;3048 3600000 1" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_airport" DATA
- Start Time: Tue Jul 11 17:23:04 2017
- Succeeded at Tue Jul 11 17:23:05 2017 (Elapsed Time: 0.53 seconds)

Extract by Mask (6)

*Tool Name:*Extract by Mask
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Extraction\ExtractByMask

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_historicplaces
Input raster or feature mask data	Input	Required	Composite Geodataset	RegionDEM_area
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_historicplaces

Messages:

- Executing (Extract by Mask (6)): ExtractByMask "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_historicplaces" RegionDEM_area "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_historicplaces"
- Start Time: Tue Jul 11 17:23:05 2017
- Succeeded at Tue Jul 11 17:23:05 2017 (Elapsed Time: 0.53 seconds)

Reclassify (6)

*Tool Name:*Reclassify
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Reclass\Reclassify

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_historicplaces
Reclass field	Input	Required	Field	VALUE
Reclassification	Input	Required	Remap	0 328.084000 0;328.084000 3600000 1
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_historicplaces
Change missing values to NoData	Input	Optional	Boolean	false

Messages:

- Executing (Reclassify (6)): Reclassify "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_historicplaces" VALUE "0 328.084000 0;328.084000 3600000 1" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_historicplaces" DATA
- Start Time: Tue Jul 11 17:23:05 2017
- Succeeded at Tue Jul 11 17:23:06 2017 (Elapsed Time: 0.52 seconds)

Extract by Mask (10)

*Tool Name:*Extract by Mask
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Extraction\ExtractByMask

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_UNDareas
Input raster or feature mask data	Input	Required	Composite Geodataset	RegionDEM_area
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_UNDareas

Messages:

Executing (Extract by Mask (10)): ExtractByMask "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_UNDareas" RegionDEM_area "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_UNDareas"

Start Time: Tue Jul 11 17:23:06 2017

Succeeded at Tue Jul 11 17:23:07 2017 (Elapsed Time: 0.53 seconds)

Reclassify (9)

*Tool Name:*Reclassify
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Reclass\Reclassify

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_UNDareas
Reclass field	Input	Required	Field	VALUE
Reclassification	Input	Required	Remap	0 10 1;10 3600000 0
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_UNDareas
Change missing values to NoData	Input	Optional	Boolean	false

Messages:

Executing (Reclassify (9)): Reclassify "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_UNDareas" VALUE "0 10 1;10 3600000 0" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_UNDareas" DATA

Start Time: Tue Jul 11 17:23:07 2017

Succeeded at Tue Jul 11 17:23:07 2017 (Elapsed Time: 0.54 seconds)

Extract by Mask (11)

*Tool Name:*Extract by Mask
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Extraction\ExtractByMask

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_floodplan
Input raster or feature mask data	Input	Required	Composite Geodataset	RegionDEM_area
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_floodplan

Messages:

Executing (Extract by Mask (11)): ExtractByMask "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_floodplan" RegionDEM_area "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_floodplan"

Start Time: Tue Jul 11 17:23:07 2017

Succeeded at Tue Jul 11 17:23:08 2017 (Elapsed Time: 0.57 seconds)

Reclassify (10)

*Tool Name:*Reclassify
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Reclass\Reclassify

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_floodplan
Reclass field	Input	Required	Field	VALUE
Reclassification	Input	Required	Remap	0 500 0;500 3600000 1
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_floodplan
Change missing values to NoData	Input	Optional	Boolean	false

Messages:

Executing (Reclassify (10)): Reclassify "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_floodplan" VALUE "0 500 0;500 3600000 1" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_floodplan" DATA

Start Time: Tue Jul 11 17:23:08 2017

Succeeded at Tue Jul 11 17:23:09 2017 (Elapsed Time: 0.53 seconds)

Extract by Mask (7)

*Tool Name:*Extract by Mask
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Extraction\ExtractByMask

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_reaches
Input raster or feature mask data	Input	Required	Composite Geodataset	RegionDEM_area
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_reaches

Messages:

Executing (Extract by Mask (7)): ExtractByMask "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_reaches" RegionDEM_area "C:\Users\jooho\Google

Drive\GISdata\BR.gdb\Extract_reaches"

- Start Time: Tue Jul 11 17:23:09 2017
- Succeeded at Tue Jul 11 17:23:09 2017 (Elapsed Time: 0.54 seconds)

Reclassify (8)

*Tool Name:*Reclassify
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Reclass\Reclassify

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_reaches
Reclass field	Input	Required	Field	VALUE
Reclassification	Input	Required	Remap	0 500 0;500 3600000 1
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_reaches
Change missing values to NoData	Input	Optional	Boolean	false

Messages:

- Executing (Reclassify (8)): Reclassify "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_reaches" VALUE "0 500 0;500 3600000 1" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_reaches" DATA
- Start Time: Tue Jul 11 17:23:09 2017
- Succeeded at Tue Jul 11 17:23:10 2017 (Elapsed Time: 0.53 seconds)

Weighted Sum

*Tool Name:*Weighted Sum
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Overlay\WeightedSum

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input rasters	Input	Required	Weighted Sum	'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_slope' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_wetland' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_school' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_emergencycare' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_hzCareFlty' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_airport' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_historicplaces' VALUE

				1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_UNDareas' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_floodplan' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_reaches' VALUE 1
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Weighte_Recl1

Messages:

- Executing (Weighted Sum): WeightedSum "'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_slope' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_wetland' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_school' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_emergencycare' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_hzCareFlty' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_airport' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_historicplaces' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_UNDareas' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_floodplan' VALUE 1;'C:\Users\jooho\Google Drive\GISdata\BR.gdb\Reclass_reaches' VALUE 1" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Weighte_Recl1"
- Start Time: Tue Jul 11 17:23:10 2017
- Succeeded at Tue Jul 11 17:23:11 2017 (Elapsed Time: 1.00 seconds)

Extract by Mask (9)

*Tool Name:*Extract by Mask
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Extraction\ExtractByMask

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_residential
Input raster or feature mask data	Input	Required	Composite Geodataset	RegionDEM_area
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_residential

Messages:

- Executing (Extract by Mask (9)): ExtractByMask "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_residential" RegionDEM_area "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_residential"
- Start Time: Tue Jul 11 17:23:11 2017
- Succeeded at Tue Jul 11 17:23:12 2017 (Elapsed Time: 0.57 seconds)

Fuzzy Membership (2)

*Tool Name:*Fuzzy Membership
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Overlay\FuzzyMembership

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_residential
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\FuzzyMe_residential
Membership type	Input	Optional	Fuzzy function	LARGE 100 5
Hedge	Input	Optional	String	NONE

Messages:

- Executing (Fuzzy Membership (2)): FuzzyMembership "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_residential" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\FuzzyMe_residential" "LARGE 100 5" NONE
- Start Time: Tue Jul 11 17:23:12 2017
- Succeeded at Tue Jul 11 17:23:13 2017 (Elapsed Time: 0.71 seconds)

Extract by Mask (8)

*Tool Name:*Extract by Mask
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Extraction\ExtractByMask

Parameters:

Name	*Direction*	*Type*	*Data Type*	*Value*
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_mainroads
Input raster or feature mask data	Input	Required	Composite Geodataset	RegionDEM_area
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_roads

Messages:

- Executing (Extract by Mask (8)): ExtractByMask "C:\Users\jooho\Google Drive\GISdata\BR.gdb\EucDist_mainroads" RegionDEM_area "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_roads"
- Start Time: Tue Jul 11 17:23:14 2017
- Succeeded at Tue Jul 11 17:23:15 2017 (Elapsed Time: 0.56 seconds)

Fuzzy Membership

*Tool Name:*Fuzzy Membership
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Overlay\FuzzyMembership

Parameters:

Name	Direction	Type	Data Type	Value
Input raster	Input	Required	Composite Geodataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_roads
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\FuzzyMe_mainroad
Membership type	Input	Optional	Fuzzy function	SMALL 500 5
Hedge	Input	Optional	String	NONE

Messages:

- Executing (Fuzzy Membership): FuzzyMembership "C:\Users\jooho\Google Drive\GISdata\BR.gdb\Extract_roads" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\FuzzyMe_mainroad" "SMALL 500 5" NONE
- Start Time: Tue Jul 11 17:23:15 2017
- Succeeded at Tue Jul 11 17:23:16 2017 (Elapsed Time: 0.61 seconds)

Raster Calculator

*Tool Name:*Raster Calculator
*Tool Source:*c:\program files (x86)\arcgis\desktop10.5\ArcToolbox\Toolboxes\Spatial Analyst Tools.tbx\Map Algebra\RasterCalculator

Parameters:

Name	Direction	Type	Data Type	Value
Map Algebra expression	Input	Required	Raster Calculator Expression	"%Weighte_Recl1%" + "%FuzzyMe_residential%" + "%FuzzyMe_mainroad%"
Output raster	Output	Required	Raster Dataset	C:\Users\jooho\Google Drive\GISdata\BR.gdb\TDMSlocations

Messages:

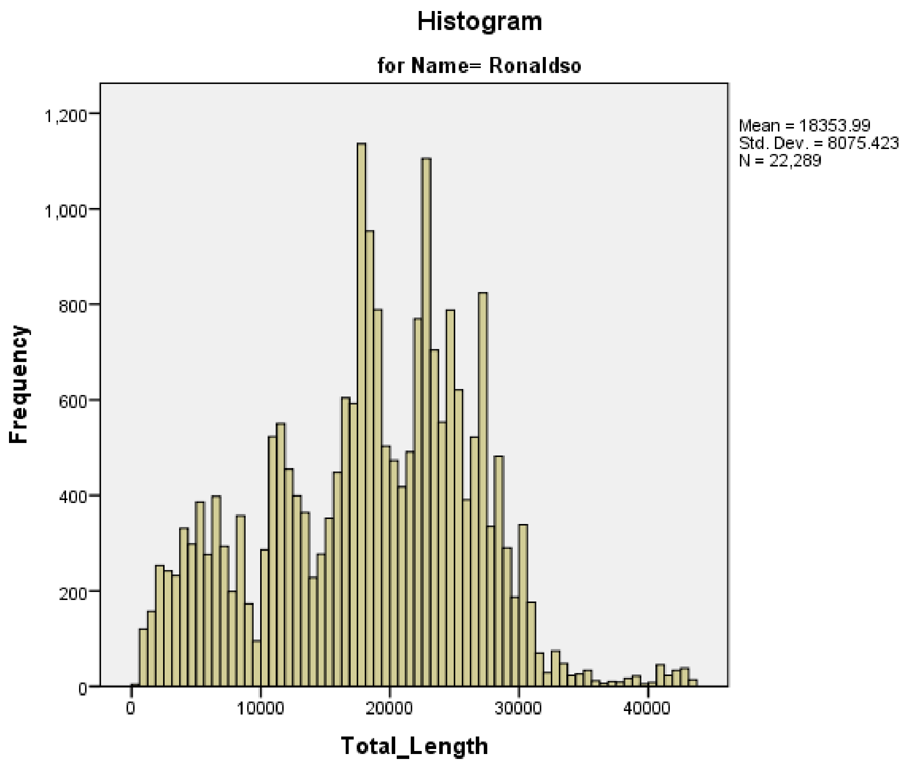
- Executing (Raster Calculator): RasterCalculator ""C:\Users\jooho\Google Drive\GISdata\BR.gdb\Weighte_Recl1" + "C:\Users\jooho\Google Drive\GISdata\BR.gdb\FuzzyMe_residential" + "C:\Users\jooho\Google Drive\GISdata\BR.gdb\FuzzyMe_mainroad"" "C:\Users\jooho\Google Drive\GISdata\BR.gdb\TDMSlocations"
- Start Time: Tue Jul 11 17:23:16 2017
- Raster(r"C:\Users\jooho\Google Drive\GISdata\BR.gdb\Weighte_Recl1") + Raster(r"C:\Users\jooho\Google Drive\GISdata\BR.gdb\FuzzyMe_residential") + Raster(r"C:\Users\jooho\Google Drive\GISdata\BR.gdb\FuzzyMe_mainroad")
- Succeeded at Tue Jul 11 17:23:17 2017 (Elapsed Time: 1.59 seconds)

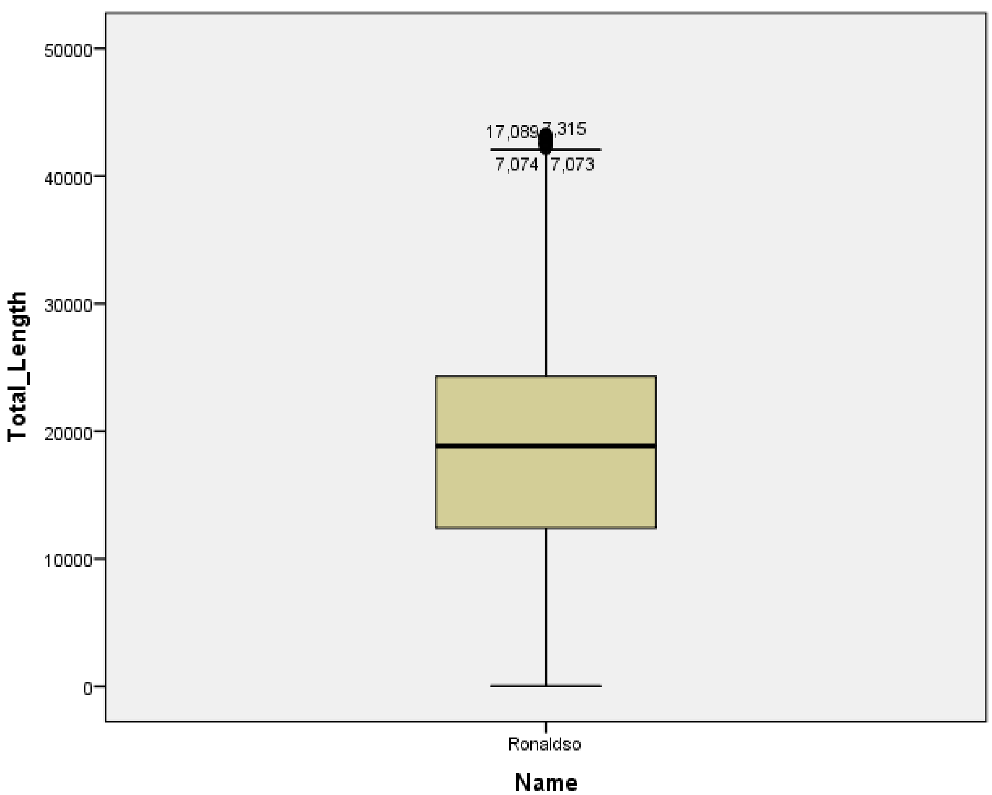
APPENDIX B. STATISTICAL ANALYSIS FOR THE SCENARIOS

Scenario#1 – 1 Landfill

Descriptive

	Name			Statistic	Std. Error
Total_Length	Ronaldso	Mean		18353.99	54.090
		95% Confidence Interval for Mean	Lower Bound	18247.97	
			Upper Bound	18460.01	
		5% Trimmed Mean		18397.65	
		Median		18847.43	
		Variance		65212452.090	
		Std. Deviation		8075.423	
		Minimum		27	
		Maximum		43312	
		Range		43285	
		Interquartile Range		11891	
		Skewness		-.175	.016
		Kurtosis		-.358	.033

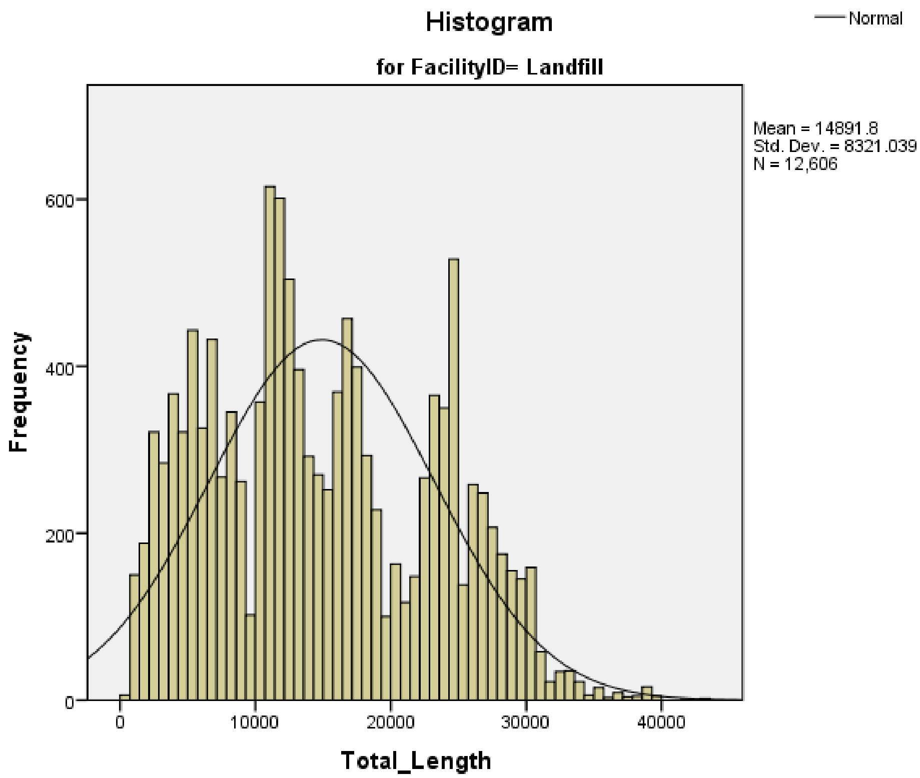

Histogram
for Name= Ronaldso
Mean = 18353.99
Std. Dev. = 8075.423
N = 22,289
Frequency
1,200
1,000
800
600
400
200
0
0
10000
20000
30000
40000
Total_Length

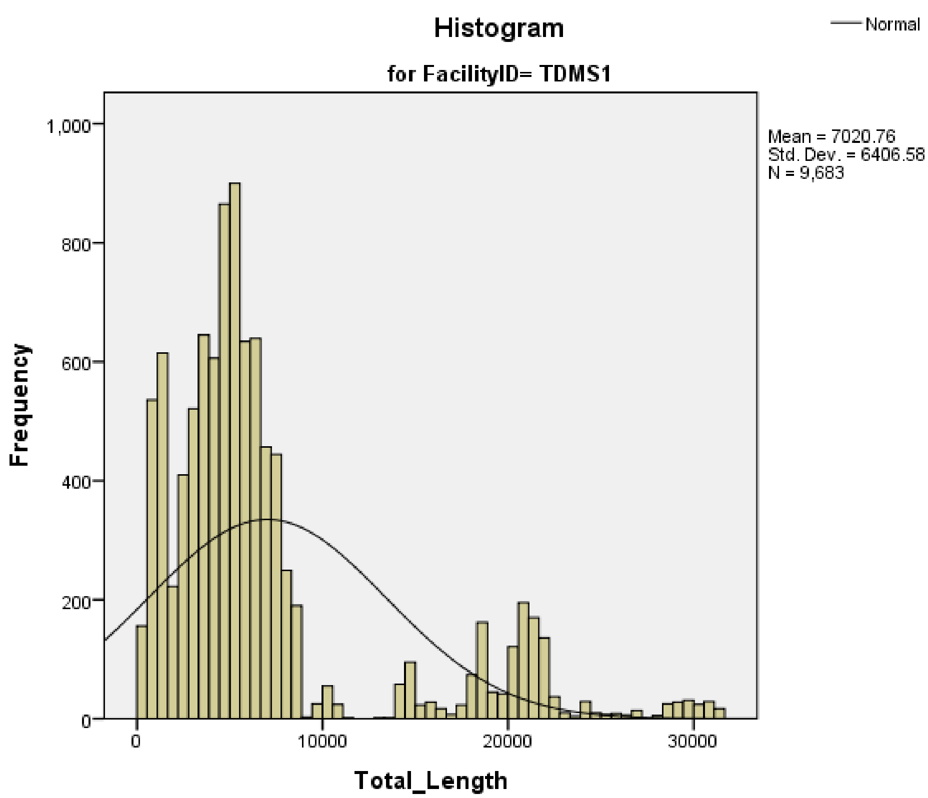

50000
40000
30000
20000
10000
0
Total_Length
17,089
7,315
7,074
7,073
Ronaldso
Name

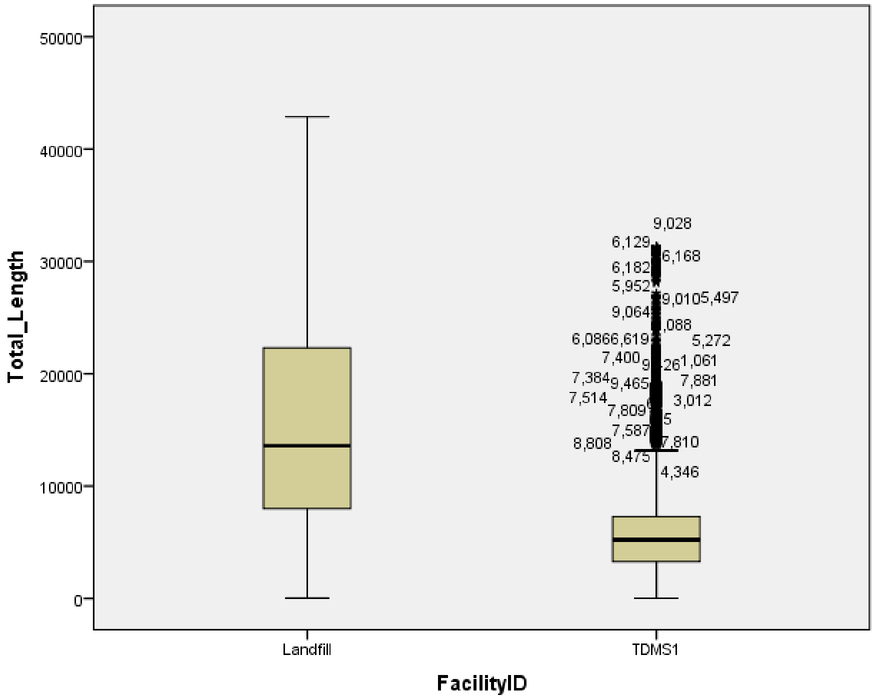
Scenario#2 – 1 TDMS and 1 Landfill

Descriptive

	FacilityID			Statistic	Std. Error
Total_Length	Landfill	Mean		14891.80	74.112
		95% Confidence Interval for Mean	Lower Bound	14746.53	
			Upper Bound	15037.07	
		5% Trimmed Mean		14706.26	
		Median		13608.17	
		Variance		69239689.180	
		Std. Deviation		8321.039	
		Minimum		27	
		Maximum		42901	
		Range		42874	
		Interquartile Range		14319	
		Skewness		.302	.022
		Kurtosis		-.844	.044
	TDMS1	Mean		7020.76	65.106
		95% Confidence Interval for Mean	Lower Bound	6893.14	
			Upper Bound	7148.38	
		5% Trimmed Mean		6372.55	
		Median		5232.25	
		Variance		41044271.250	
		Std. Deviation		6406.580	
		Minimum		13	
		Maximum		31330	
		Range		31317	
		Interquartile Range		3999	
		Skewness		1.783	.025
		Kurtosis		2.502	.050


Histogram
Normal
for FacilityID= Landfill
Mean = 14891.8
Std. Dev. = 8321.039
N = 12,606
Frequency
600
400
200
0
0
10000
20000
30000
40000
Total_Length


Histogram
Normal
for FacilityID= TDMS1
Mean = 7020.76
Std. Dev. = 6406.58
N = 9,683
Frequency
1,000
800
600
400
200
0
0
10000
20000
30000
Total_Length



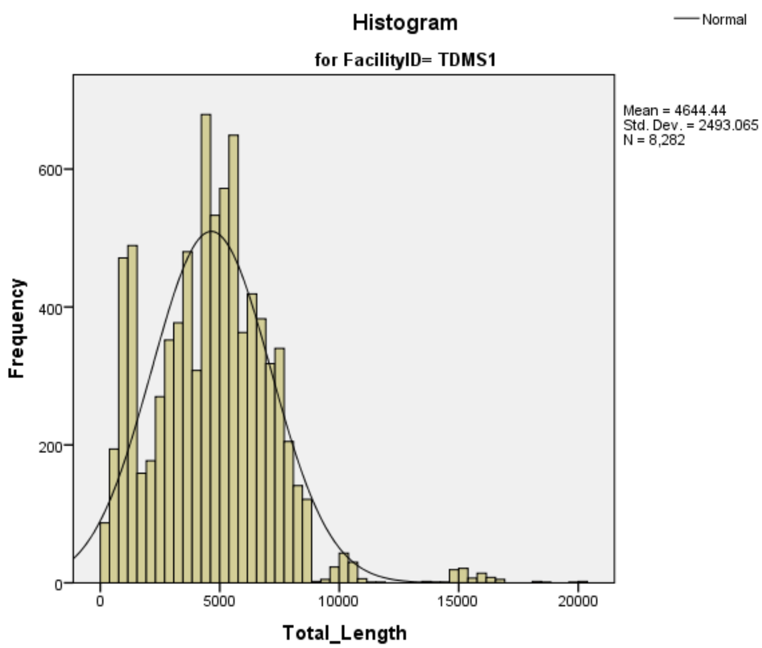
50000
40000
30000
20000
10000
0
Total_Length
Landfill
TDMS1
FacilityID
9,028
6,129
6,168
6,182
5,952
5,497
9,064
5,272
7,400
1,061
7,384
9,465
7,881
7,514
3,012
7,809
7,587
8,808
7,810
8,475
4,346

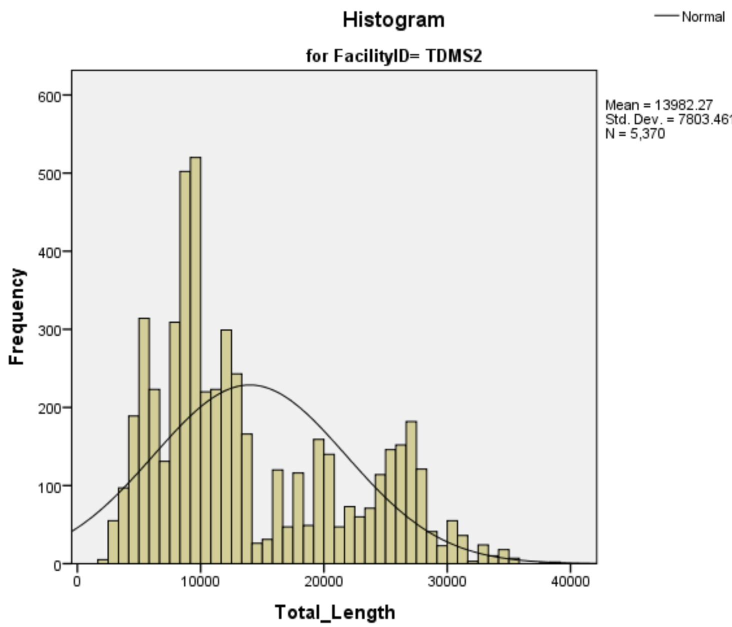
Scenario#3 – 2 TDMS and 1 Landfill

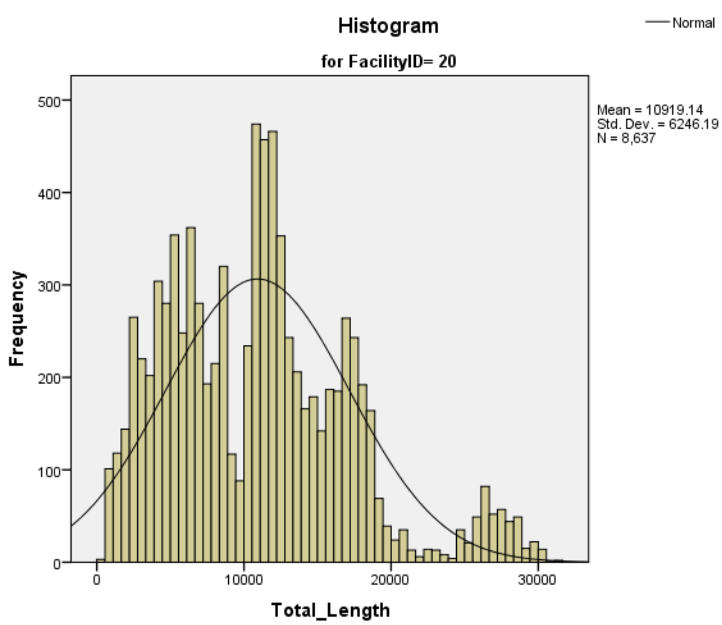
Descriptive

	FacilityID			Statistic	Std. Error
Total_Length	TDMS1	Mean		4644.44	27.395
		95% Confidence Interval for Mean	Lower Bound	4590.74	
			Upper Bound	4698.14	
		5% Trimmed Mean		4548.71	
		Median		4683.97	
		Variance		6215370.819	
		Std. Deviation		2493.065	
		Minimum		13	
		Maximum		20164	
		Range		20151	
		Interquartile Range		3273	
		Skewness		.808	.027
		Kurtosis		2.786	.054
	TDMS2	Mean		13982.27	106.488
		95% Confidence Interval for Mean	Lower Bound	13773.51	
			Upper Bound	14191.03	
		5% Trimmed Mean		13614.59	
		Median		11322.28	
		Variance		60894002.160	
		Std. Deviation		7803.461	
		Minimum		2007	
		Maximum		39007	
		Range		37000	
		Interquartile Range		11490	
		Skewness		.757	.033
		Kurtosis		-.590	.067
	20	Mean		10919.14	67.210
		95% Confidence Interval for Mean	Lower Bound	10787.39	
			Upper Bound	11050.89	
		5% Trimmed Mean		10530.01	
		Median		10881.85	
		Variance		39014894.430	

	Std. Deviation	6246.190	
	Minimum	27	
	Maximum	31310	
	Range	31283	
	Interquartile Range	8743	
	Skewness	.728	.026
	Kurtosis	.390	.053




Histogram
Normal
for FacilityID= TDMS2
Mean = 13982.27
Std. Dev. = 7803.461
N = 5,370
Frequency
Total_Length


Histogram
Normal
for FacilityID= 20
Mean = 10919.14
Std. Dev. = 6246.19
N = 8,637
Frequency
Total_Length

APPENDIX C. ANYLOGIC PROCESS MOMDELING LIBRARY BLOCKS

Source	Generates agents.
Sink	Disposes incoming agents.
Delay	Delays agents by the specified delay time.
Queue	Stores agents in the specified order.
SelectOutput	Forwards the agent to one of the output ports depending on the condition.
SelectOutput5	Routes the incoming agents to one of the five output ports depending on (probabilistic or deterministic) conditions.
Hold	Blocks/unblocks the agent flow.
Match	Finds a match between two agents from different inputs, then outputs them.
Split	For each incoming agent ("original") creates one or several other agents-copies.
Combine	Waits for two agents, then produces a new agent from them.
Assembler	Assembles a certain number of agents from several sources (5 or less) into a single agent.
MoveTo	Moves an agent from its current location to new location.
Conveyor	Moves agents at a certain speed, preserving order and space between them.
ResourcePool	Provides resource units that are seized and released by agents.
Seize	Seizes the number of units of the specified resource required by the agent.
Release	Releases resource units previously seized by the agent.
Service	Seizes resource units for the agent, delays it, and releases the seized units.

ResourceSendTo	Sends a set of portable and/or moving resources to specified location.
ResourceTaskStart	Defines the start of the flowchart branch modeling the task process for resource units (usually it is a resource preparation process).
ResourceTaskEnd	Defines the end of the flowchart branch modeling the task process for resource unit(s) (usually it is a wrap-up process).
ResourceTask	Defines some custom task for resources that cannot be defined using the provided standard patterns for failures, maintenance, breaks.
Enter	Inserts agents created elsewhere into the flowchart.
Exit	Accepts incoming agents.
Batch	Accumulates agents, then outputs them contained in a new agent.
Unbatch	Extracts all agents contained in the incoming agent and outputs them.
Dropoff	Extracts the selected agents from the contents of the incoming agent.
Pickup	Adds the selected agents to the contents of the incoming agent.
RestrictedAreaStart	Limits number of agents in a part of flowchart between corresponding area start and area end blocks.
RestrictedAreaEnd	Ends an area started with RestrictedAreaStart block.
TimeMeasureStart	**TimeMeasureStart** as well as **TimeMeasureEnd** compose a pair of objects measuring the time the agents spend between them, such as "time in system", "length of stay", etc. This object remembers the time when an agent goes through.
TimeMeasureEnd	**TimeMeasureEnd** as well as **TimeMeasureStart** compose a pair of objects measuring the time the agents spend between them.

For each incoming agent this object measures the time it spent since it has been through one of the corresponding **TimeMeasureStart** objects.

ResourceAttach Attaches a set of portable and/or moving resources to the agent.

ResourceDetach Detaches previously attached resources from the agent.

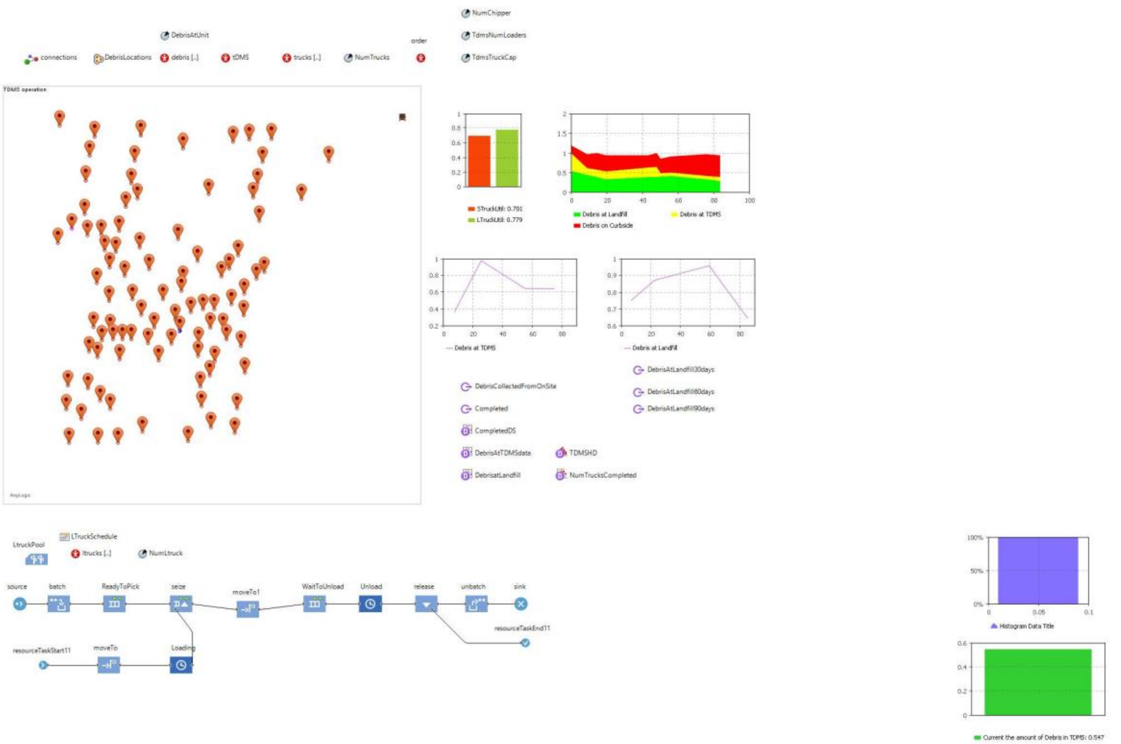
APPENDIX D. DESCRIPTION OF THE SIMULATION MODEL IN THE STUDY

Model: Simulation1

null	null
General	
Model time units	hours
Numerical methods	
Differention Equations Method	Euler
Algebraic Equations Method	Modified Newton
Mixed Equations Method	RK45+Newton
Absolute accuracy	1.0E-5
Time accuracy	1.0E-5
Relative accuracy	1.0E-5
Fixed time step	0.001
Advanced	
Java package name	cbr2019
File Name	C:\Users\jooho\Google Drive\7. Ph.D research\Simulation\Simulation1\Simulation1.alp

Agent Type: main

null	null
Agent in flowcharts	
Use in flowcharts as	Agent
Movement	
Speed	(10 : MPS)
Rotate animation towards movement	true
Rotate vertically as well (along Z-axis)	false
Space and network	
Enable steps	false
Advanced Java	
Import	import com.bbn.openmap.gui.NavigatePanel;
Generic	false
Advanced	
Logging	true
Auto-create datasets	true
AOC_DATASETS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Limit the number of data samples	false



Scale: scale

null	null
General	
Unit	meter
Scale	10.0
Type	Defined graphically
Length, pixels	100.0
Show at runtime	false
Lock	false
Public	false
Position and size	
x	0.0
y	-150.0
Rotation	0.0

Parameter: NumTrucks

null	null

null	null
General	
Array	false
Type	int
Show at runtime	true
Show name	true
Value editor	
Editor control	Text
Advanced	
System dynamics units	false
Save in snapshot	true

Parameter: NumLtruck

null	null
General	
Array	false
Type	int
Show at runtime	true
Show name	true
Value editor	
Editor control	Text
Advanced	
System dynamics units	false
Save in snapshot	true

Parameter: TdmsTruckCap

null	null
General	
Array	false
Type	int
Show at runtime	true
Show name	true
Value editor	
Editor control	Text
Advanced	
System dynamics units	false
Save in snapshot	true

Parameter: TdmsNumLoaders

null	null
General	
Array	false
Type	int
Show at runtime	true

null	null
Show name	true
Value editor	
Editor control	Text
Advanced	
System dynamics units	false
Save in snapshot	true

Parameter: DebrisAtUnit

null	null
General	
Array	false
Type	int
Show at runtime	true
Show name	true
Value editor	
Editor control	Text
Advanced	
System dynamics units	false
Save in snapshot	true

Parameter: NumChipper

null	null
General	
Array	false
Type	int
Show at runtime	true
Show name	true
Value editor	
Editor control	Text
Advanced	
System dynamics units	false
Save in snapshot	true

Schedule: LTruckSchedule

null	null
General	
Show at runtime	true
Show name	true
Data	
Value type	on/off
The schedule defines	Intervals (Start, End)
Representation type	Week

null	null
Default value	false
Preview	
SCHEDULE_PREVIEW_START_DATE	1523624943422
Advanced	
System dynamics units	false

Sun	Mon	Tue	We	Thu	Fri	Sat	null	null	null
+	+	+	+	+	+	+	6:00 AM	6:00 PM	true

Collection: DebrisLocations

null	null
General	
Initial contents	{ gisPoint74, gisPoint17, gisPoint35, gisPoint43, gisPoint77, gisPoint69, gisPoint1, gisPoint34, gisPoint42, gisPoint37, gisPoint23, gisPoint45, gisPoint81, gisPoint28, gisPoint36, gisPoint39, gisPoint80, gisPoint18, gisPoint68, gisPoint72, gisPoint78, gisPoint75, gisPoint20, gisPoint, gisPoint22, gisPoint25, gisPoint24, gisPoint56, gisPoint9, gisPoint2, gisPoint61, gisPoint7, gisPoint31, gisPoint53, gisPoint5, gisPoint48, gisPoint86, gisPoint41, gisPoint57, gisPoint16, gisPoint4, gisPoint73, gisPoint13, gisPoint30, gisPoint26, gisPoint15, gisPoint71, gisPoint79, gisPoint64, gisPoint11, gisPoint3, gisPoint82, gisPoint65, gisPoint63, gisPoint52, gisPoint85, gisPoint84, gisPoint46, gisPoint38, gisPoint21, gisPoint66, gisPoint44, gisPoint59, gisPoint51, gisPoint62, gisPoint27, gisPoint29, gisPoint58, gisPoint60, gisPoint47, gisPoint6, gisPoint54, gisPoint8, gisPoint40, gisPoint67, gisPoint33, gisPoint12, gisPoint83, gisPoint55, gisPoint76, gisPoint70, gisPoint10, gisPoint14, gisPoint49, gisPoint32, gisPoint50, gisPoint19, gisPoint87, gisPoint88, gisPoint89 }
Initial contents	{ gisPoint74, gisPoint17, gisPoint35, gisPoint43, gisPoint77, gisPoint69, gisPoint1, gisPoint34, gisPoint42, gisPoint37, gisPoint23, gisPoint45, gisPoint81, gisPoint28, gisPoint36, gisPoint39, gisPoint80, gisPoint18, gisPoint68, gisPoint72, gisPoint78, gisPoint75, gisPoint20, gisPoint, gisPoint22, gisPoint25, gisPoint24, gisPoint56, gisPoint9, gisPoint2, gisPoint61, gisPoint7, gisPoint31, gisPoint53, gisPoint5, gisPoint48, gisPoint86, gisPoint41, gisPoint57, gisPoint16, gisPoint4, gisPoint73, gisPoint13, gisPoint30, gisPoint26, gisPoint15, gisPoint71, gisPoint79, gisPoint64, gisPoint11, gisPoint3, gisPoint82, gisPoint65, gisPoint63, gisPoint52, gisPoint85, gisPoint84, gisPoint46, gisPoint38, gisPoint21, gisPoint66, gisPoint44, gisPoint59, gisPoint51, gisPoint62, gisPoint27, gisPoint29, gisPoint58, gisPoint60, gisPoint47, gisPoint6, gisPoint54, gisPoint8, gisPoint40, gisPoint67, gisPoint33, gisPoint12, gisPoint83, gisPoint55, gisPoint76, gisPoint70, gisPoint10, gisPoint14, gisPoint49, gisPoint32, gisPoint50, gisPoint19, gisPoint87, gisPoint88, gisPoint89 }
Element class	GISPoint
Collection class	ArrayList
Show at runtime	true
Show name	true
Advanced	
Access type	public
Save in snapshot	true
Static	false

Debris: debris

null	null
General	
Replication	DebrisLocations.size()
Initialization Type	Contains a given number of agents
Population of agents	true
Replication	DebrisLocations.size()
Initialization Type	Contains a given number of agents
Population of agents	true
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	in the node
Node	DebrisLocations.get(index)
Node	DebrisLocations.get(index)
Statistics	
Statistics	[]
Advanced	
Show at runtime	true
Public	false
Embedded object collection type	Access by index (ArrayList)
Logging	true

null	null
Constant	0.01
TotalPopulation	1

TDMS: tDMS

null	null
General	
Population of agents	false
Population of agents	false
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	in the node
Node	TDMS
Node	TDMS
Advanced	
Show at runtime	true
Public	false

null	null
Logging	true

Truck: trucks

null	null
General	
Replication	NumTrucks
Initialization Type	Contains a given number of agents
Population of agents	true
Replication	NumTrucks
Initialization Type	Contains a given number of agents
Population of agents	true
Show name	true
Movement	
Initial Speed Code	(25 : MPH)
Initial location	
Place agent(s)	in the node
Node	TDMS
Node	TDMS
Statistics	
Statistics	[]
Advanced	
Show at runtime	true
Public	false
Embedded object collection type	Access by index (ArrayList)
Logging	true

Source: source

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Arrivals defined by	self.MANUAL
New agent	new Agent()
Location of arrival	self.LOCATION_NODE
Node	TDMS
Speed	10
Add agents to:	false
Forced pushing	true

Ltrucks: ltrucks

null	null
General	
Replication	NumLtruck
Initialization Type	Contains a given number of agents
Population of agents	true
Replication	NumLtruck
Initialization Type	Contains a given number of agents
Population of agents	true
Show name	true
Movement	
Initial Speed Code	(40 : MPH)
Initial location	
Place agent(s)	at the agent animation location
Statistics	
Statistics	[]
Advanced	
Show at runtime	true
Public	false
Embedded object collection type	Access by index (ArrayList)
Logging	true

ResourcePool: LtruckPool

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location

null	null
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Resource type	self.RESOURCE_MOVING
Capacity defined	self.CAPACITY_SCHEDULE_ON_OFF
On/off schedule	LTruckSchedule
Capacity when "On"	NumLtruck
When capacity decreases	false
New resource unit	new cbr2019.Ltrucks()
Speed	10
Home location is	self.HOME_SINGLE_NODE
Home location (nodes)	{ landfill }
'End of shift' priority	100
'End of shift' preemption policy	self.PP_NO_PREEMPTION
'End of shift' may preempt	true
Breaks	false
Failures / repairs	false
Maintenance	false
Custom tasks	false
Add units to:	false
Force statistics collection	false

MoveTo: moveTo

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null

null	null
Agent	self.MODE_MOVE_TO
Destination:	self.DEST_NODE
Node	TDMS
... with offset	false
Straight movement	false
Movement is defined by:	self.MOVE_SPEED
Set agent's speed	false

MoveTo: moveTo1

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Agent	self.MODE_MOVE_TO
Destination:	self.DEST_NODE
Node	landfill
... with offset	false
Straight movement	false
Movement is defined by:	self.MOVE_SPEED
Set agent's speed	false

Delay: Unload

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]

null	null
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Type	self.TIMEOUT
Delay time	triangular(10, 15, 20)
Maximum capacity	true
Forced pushing	false
Restore agent location on exit	true
Force statistics collection	false

Sink: sink

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Destroy policy:	com.anylogic.libraries.processmodeling.Sink.DESTROY_ONLY_CREATED_IN_SOURCE

ResourceTaskEnd: resourceTaskEnd11

null	null
General	

null	null
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Move resource to its home location	true
Release resources seized by this unit	true

ResourceTaskStart: resourceTaskStart11

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Ltrucks]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Ltrucks]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Start here:	true

Seize: seize

null	null
General	
Population of agents	false

null	null
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Seize	true
Resource pool	LtruckPool
Number of units	1
Seize policy	self.SEIZE_WHOLE_SET
Maximum queue capacity	true
Send seized resources	true
Destination is	self.DEST_NODE
Node	landfill
Attach seized resources	true
Task priority	0
Task may preempt	true
Task preemption policy	self.PP_NO_PREEMPTION
Customize resource choice	false
Define preparation tasks by	true
Enable exit on timeout	false
Enable preemption	false
Canceled units:	self.CANCELED_UNITS_STAY_WHERE_THEY_ARE
Forced pushing	false
Restore agent location on exit	true
Force statistics collection	false
"agent1 is preferred to agent2"	false

Release: release

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]

null	null
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Release	self.ALL
Moving resources	true
Wrap-up (e.g. move home)	self.WRAP_UP_ALWAYS
'Wrap-up' usage statistics are:	self.USAGE_BUSY

Order: order

null	null
General	
Population of agents	false
Population of agents	false
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Queue: WaitToUnload

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location

null	null
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Capacity	100
Maximum capacity	false
Queuing	self.QUEUING_FIFO
Enable exit on timeout	false
Enable preemption	false
Restore agent location on exit	true
Force statistics collection	false

Batch: batch

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: , Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: , Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Batch size	2
Permanent batch	false
New batch	new Agent()
Agent location	TDMS
Location of batch	self.LOCATION_NOT_SPECIFIED
Add batches to:	false
Forced pushing	false
Restore agent location on exit	true
Force statistics collection	false

Unbatch: unbatch

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: , Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: , Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Forced pushing	false

Delay: Loading

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Type	self.TIMEOUT
Delay time	triangular(3, 5, 10)
Maximum capacity	true
Forced pushing	false
Restore agent location on exit	true
Force statistics collection	false

Queue: ReadyToPick

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Maximum capacity	true
Queuing	self.QUEUING_FIFO
Enable exit on timeout	false
Enable preemption	false
Restore agent location on exit	true
Force statistics collection	false

Bar Chart: EquipUtilization

null	null
General	
Chart Scale: To	1
Chart Scale: From	0
Scale type	Fixed
Public	true
Data update	
Analysis auto update	true
ANALYSIS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Appearance	
Bars relative width	0.8
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Position and size	
x	780.0
Width	190.0

null	null
y	20.0
Height	230.0
Legend	
Show legend	true
Legend size	40.0
Legend text color	black
Chart area	
Chart Area: X Offset	50.0
Chart Area: Width	100.0
Chart Area: Y Offset	30.0
Chart Area: Height	130.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false

null	null	null
STruckUtil	new Color(247, 68, 8)	tDMS.trucks.utilization()
LTruckUtil	yellowGreen	LtruckPool.utilization()

Bar Chart: chart1

null	null
General	
Scale type	Auto
Public	true
Data update	
Analysis auto update	true
ANALYSIS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Appearance	
Bars relative width	0.8
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Position and size	
x	1690.0
Width	320.0
y	970.0
Height	220.0
Legend	
Show legend	true
Legend size	30.0
Legend text color	black
Chart area	

null	null
Chart Area: X Offset	50.0
Chart Area: Width	240.0
Chart Area: Y Offset	30.0
Chart Area: Height	130.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false

null	null	null
Current the amount of Debris in TDMS	limeGreen	(ReadyToPick.in.count()-ReadyToPick.out.count())*50 //seize.size()//+seize1.size()

Time Plot: chart2

null//seize.size()*50//+seize1.size()

null	null
General	
Public	true
Data update	
Analysis auto update	true
ANALYSIS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Dataset Samples To Keep	1000
Scale	
Time window	90
Time	days
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Label format	Model time units
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	true
Fill area under line	false
Interpolation	Linear
Position and size	
x	1060.0
Width	320.0
y	280.0
Height	210.0
Legend	
Show legend	true
Legend size	30.0

null	null
Legend text color	black
Chart area	
Chart Area: X Offset	50.0
Chart Area: Width	240.0
Chart Area: Y Offset	30.0
Chart Area: Height	120.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Time window moves	Continuously
Show name	false
Logging	true
Description	
Description	//seize.size()*50//+seize1.size()

null	null	null	null	null	null	null	null
Debris at Landfill	value	sink.count()*25	NONE	mediumOrchid	true	1.0	LINEAR

Time Plot: chart3

null//seize.size()*50//+seize1.size()

null	null
General	
Public	true
Data update	
Analysis auto update	true
ANALYSIS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Dataset Samples To Keep	1000
Scale	
Time window	90
Time	days
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Label format	Model time units
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	true
Fill area under line	false
Interpolation	Linear
Position and size	
x	740.0

null	null
Width	320.0
y	280.0
Height	210.0
Legend	
Show legend	true
Legend size	30.0
Legend text color	black
Chart area	
Chart Area: X Offset	50.0
Chart Area: Width	240.0
Chart Area: Y Offset	30.0
Chart Area: Height	120.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Time window moves	Continuously
Show name	false
Logging	true
Description	
Description	//seize.size()*50//+seize1.size()

null	null	null	null	null	null	null	null
Debris at TDMS	value	(seize.in.count()-seize.out.count())*50+tDMS.RecycableMaterials.size()*25 //(ReadyToPick.in.count()-ReadyToPick.out.count())*50 //(source.count()-seize.out.count()*2)*25	NONE	mediumOrchid	true	1.0	LINEAR

Time Stack Chart: chart

null	null
General	
Public	true
Data update	
Analysis auto update	true
ANALYSIS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Dataset Samples To Keep	100
Scale	
Time window	100
Time	model time units
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT

null	null
Labels vertical position	DEFAULT
Label format	Model time units
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Position and size	
x	970.0
Width	400.0
y	20.0
Height	240.0
Legend	
Show legend	true
Legend size	40.0
Legend text color	black
Chart area	
Chart Area: X Offset	50.0
Chart Area: Width	320.0
Chart Area: Y Offset	30.0
Chart Area: Height	140.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Time window moves	Continuously
Show name	false
Logging	true

null	null	null	null
Debris at Landfill	value	sink.count()*25	lime
Debris at TDMS	value	(seize.in.count()-seize.out.count())*50+tDMS.RecycableMaterials.size()*25	yellow
Debris on Curbside	value	tDMS.enter.count()-tDMS.sink.count()	red

Histogram: chart4

null	null
General	
Show mean	false
Show CDF	false
Show PDF	true
Public	true
Data update	
Analysis auto update	false
Appearance	
Bars relative width	0.8
Labels vertical position	DEFAULT

null	null
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Position and size	
x	1720.0
Width	260.0
y	780.0
Height	210.0
Legend	
Show legend	true
Legend size	30.0
Legend text color	black
Chart area	
Chart Area: X Offset	50.0
Chart Area: Width	180.0
Chart Area: Y Offset	30.0
Chart Area: Height	120.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false

null	null	null	null	null	null	null	null
Histogram Data Title	TDMSHD	lightSlateBlue	limeGreen	darkMagenta	1	orange	goldenRod

Data Set: DebrisAtTDMSdata

null	null
General	
Dataset Samples To Keep	10000
Axis Data Vertical Y Axis	(seize.in.count()-seize.out.count())*50+tDMS.RecycableMaterials.size()*25
Axis Data Freeze X Axis	true
Show at runtime	true
Show name	true
Data update	
Analysis auto update	true
ANALYSIS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Logging	true

Data Set: DebrisatLandfill

null	null
General	
Dataset Samples To Keep	10000

null	null
Axis Data Vertical Y Axis	sink.count()*25
Axis Data Freeze X Axis	true
Show at runtime	true
Show name	true
Data update	
Analysis auto update	true
ANALYSIS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Logging	true

Histogram Data: TDMSHD

null	null
General	
Logging	true
Calculate percentilies	false
Calculate CDF	true
Number of intervals	1
Value	//(seize.in.count()-seize.out.count())*50+tDMS.RecycableMaterials.size()*25 //tDMS.trucks.utilization()
Show at runtime	true
Show name	true
Values range	
Data range	true
Initial interval size	0.1
Data update	
Analysis auto update	true
ANALYSIS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties

Histogram2D Data: NumTrucksCompleted

null	null
General	
Envelopes	0.25, 0.5, 0.75
Axis Data Freeze X Axis	false
Show at runtime	true
Show name	true
X-axis values range	
Horizontal intervals	20
Horizontal Range: From	0
Horizontal Range: To	1
Y-axis values range	
Vertical intervals	20
Vertical Range: From	0

null	null
Vertical Range: To	1
Data update	
Analysis auto update	true
ANALYSIS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties

Data Set: CompletedDS

null	null
General	
Dataset Samples To Keep	10000
Axis Data Vertical Y Axis	tDMS.sink.count()*100/tDMS.enter.count()
Axis Data Freeze X Axis	true
Show at runtime	true
Show name	true
Data update	
Analysis auto update	true
ANALYSIS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Logging	true

Agent Presentation: debris_presentation

null	null
General	
Show at runtime	true
Public	true
Position and size	
Latitude	30.656219248897532
Longitude	-90.81615417998928
Rotation	0.0
Scale	Automatically calculated
Real size when map scale is under	1000
Fixed size when map scale is under	1000000000
Advanced	
Show in	2D and 3D
Draw agent with offset to this position	false
Show name	false

Agent Presentation: tDMS_presentation

null	null
General	
Show at runtime	true
Public	true
Position and size	

null	null
Latitude	30.42259590914518
Longitude	-90.59843901485883
Rotation	0.0
Scale	Automatically calculated
Real size when map scale is under	1000
Fixed size when map scale is under	1000000000
Advanced	
Show in	2D and 3D
Draw agent with offset to this position	false
Show name	false

Agent Presentation: trucks_presentation

null	null
General	
Show at runtime	true
Public	true
Position and size	
Latitude	30.657636295953136
Longitude	-90.85486519926218
Rotation	0.0
Scale	Automatically calculated
Real size when map scale is under	1000
Fixed size when map scale is under	1000000000
Advanced	
Show in	2D and 3D
Draw agent with offset to this position	false
Show name	false

Agent Presentation: ltrucks_presentation

null	null
General	
Show at runtime	true
Public	true
Position and size	
Latitude	30.655038360482653
Longitude	-90.78595409403184
Rotation	0.0
Scale	Automatically calculated
Real size when map scale is under	1000
Fixed size when map scale is under	1000000000
Advanced	
Show in	2D and 3D
Draw agent with offset to this position	false

null	null
Show name	false

Text: text

null	null
General	
Show at runtime	true
Lock	false
Embedded icon	false
Public	true
Text	
Text	TDMS operation
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	0.0
y	0.0
z	0.0
Rotation	0.0
Advanced	
Show in	2D only
Show name	false

GIS Map: BRmap

null	null
General	
Show at runtime	true
Lock	false
Public	true
Tiles	
Show tiles	true
Tile provider	AnyLogic
Routing	
Routes are	Requested from OSM server
Routing server	AnyLogic
Routing method	Fastest
Road type	Car
If route not found	Create straight route
Center and scale	
Latitude	30.510459089941513
Longitude	-91.04243564892109
Scale	200000
Appearance	

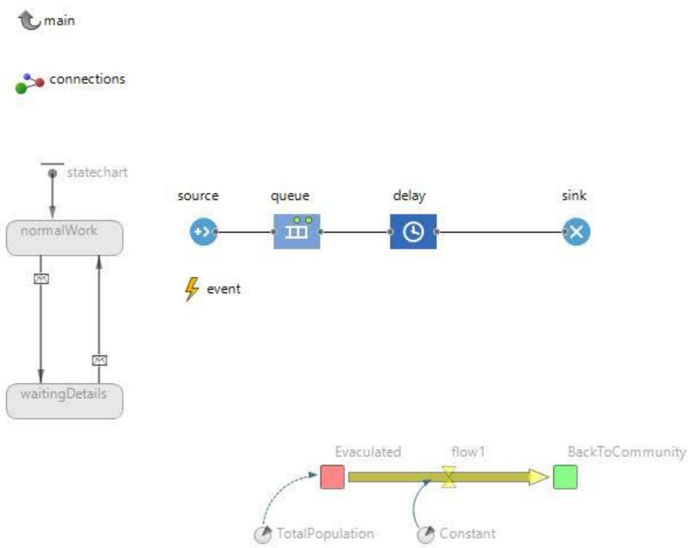
null	null
Border color	silver
Fill color	white
Position and size	
x	0.0
Width	750.0
y	0.0
Height	750.0
Advanced	
Use custom tile URL	false
Use custom route provider	false
Routes and regions generalization uses Current map scale	true

Link to agents: connections

null	null
General	
Show at runtime	true
Show name	true
Communication	
Message type	Object
Animation	
Draw line	false

Agent Type: Debris

null	null
Agent actions	
Startup code	//source.inject(400);
Agent in flowcharts	
Use in flowcharts as	Agent
Movement	
Speed	(10 : MPS)
Rotate animation towards movement	true
Rotate vertically as well (along Z-axis)	false
Space and network	
Space Type	Continuous
Advanced Java	
Generic	false
Advanced	
Logging	true
Auto-create datasets	true
AOC_DATASETS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Limit the number of data samples	false



Scale: scale

null	null
General	
Unit	meter
Scale	10.0
Type	Defined graphically
Length, pixels	100.0
Show at runtime	false
Lock	false
Public	false
Position and size	
x	0.0
y	-150.0
Rotation	0.0

Event: event

null	null
General	
Logging	true
EVENT_TIMEOUT_PROPERTIES	- Recurring Event Properties
Mode	Occurs once
Trigger type	Timeout
Show at runtime	true
Show name	true

null	null
Action	
Action	source.inject(main.DebrisAtUnit);

Source: source

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Arrivals defined by	self.MANUAL
New agent	new Agent()
Location of arrival	self.LOCATION_NOT_SPECIFIED
Add agents to:	false
Forced pushing	true

Queue: queue

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false

null	null
Logging	true

null	null
Maximum capacity	true
Queuing	self.QUEUING_FIFO
Enable exit on timeout	false
Enable preemption	false
Restore agent location on exit	true
Force statistics collection	false

Delay: delay

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Type	self.TIMEOUT
Delay time	triangular(3, 10, 6)
Capacity	5
Maximum capacity	false
Forced pushing	false
Restore agent location on exit	true
Force statistics collection	false

Sink: sink

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false

null	null
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
On enter	Order order = new Order(this); //create an order above send(order, main.tDMS); //send the order to tDMS //main.source.inject(1); //send ("OrderRequest", agent);
Destroy policy:	com.anylogic.libraries.processmodeling.Sink.DESTROY_ONLY_CREATED_IN_SOURCE

3D Object: box_opened

null	null
General	
Scale	2.0
Auto scale	true
File Name	x3d/box_opened.x3d
Show at runtime	true
Lock	false
Public	true
Position and size	
x	0.0
y	0.0
z	0.0
Rotation	0.0
Advanced	
Show in	2D and 3D
Enable AnyLogic light shaders	true
Show name	false

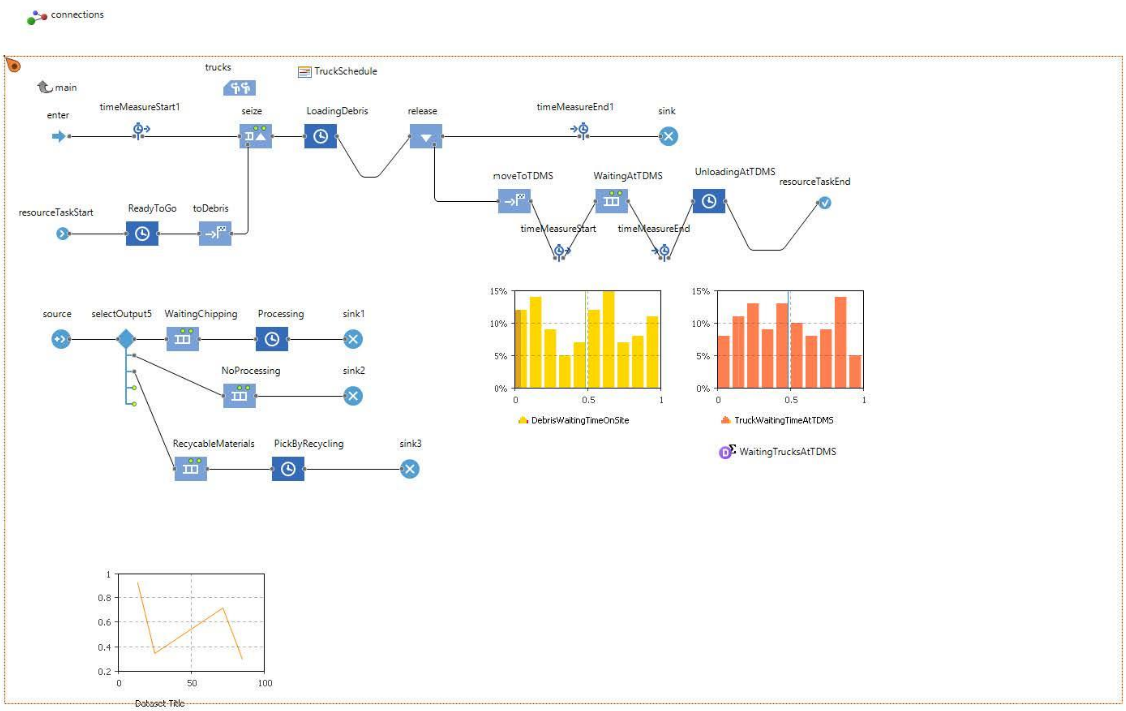
Link to agents: connections

null	null

null	null
General	
Show at runtime	true
Show name	true
Communication	
Message type	Object
Animation	
Draw line	false

Agent Type: TDMS

null	null
Agent in flowcharts	
Use in flowcharts as	Agent
Movement	
Speed	(10 : MPS)
Rotate animation towards movement	true
Rotate vertically as well (along Z-axis)	false
Space and network	
Space Type	Continuous
Advanced Java	
Generic	false
Advanced	
Logging	true
Auto-create datasets	true
AOC_DATASETS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Limit the number of data samples	false



Scale: scale

null	null
General	
Unit	mile
Scale	5.0
Type	Specified explicitly
Length, pixels	100.0
Show at runtime	false
Lock	false
Public	false
Position and size	
x	30.0
y	-100.0
Rotation	0.0

Schedule: TruckSchedule

null	null
General	

null	null
Show at runtime	true
Show name	true
Data	
Value type	on/off
The schedule defines	Intervals (Start, End)
Representation type	Week
Default value	false
Preview	
SCHEDULE_PREVIEW_START_DATE	1523624943657
Advanced	
System dynamics units	false

Sun	Mon	Tue	We	Thu	Fri	Sat	null	null	null
+	+	+	+	+	+	+	6:00 AM	6:00 PM	true

Enter: enter

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Order]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Order]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
New location	self.LOCATION_NOT_SPECIFIED
Add newborns to:	false
Forced pushing	true

Seize: seize

null	null
General	
Population of agents	false

null	null
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Seize	false
Resource sets	{ { trucks } }
Seize policy	self.SEIZE_WHOLE_SET
Maximum queue capacity	true
Send seized resources	false
Attach seized resources	false
Task priority	0
Task may preempt	true
Task preemption policy	self.PP_NO_PREEMPTION
Customize resource choice	false
Define preparation tasks by	true
Enable exit on timeout	false
Enable preemption	false
Canceled units:	self.CANCELED_UNITS_STAY_WHERE_THEY_ARE
Forced pushing	false
Restore agent location on exit	true
Force statistics collection	false
On seize unit	((Truck) unit).client = agent.customer;
"agent1 is preferred to agent2"	false

ResourcePool: trucks

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true

null	null
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Resource type	self.RESOURCE_MOVING
Capacity defined	self.CAPACITY_SCHEDULE_ON_OFF
On/off schedule	TruckSchedule
Capacity when "On"	main.NumTrucks
When capacity decreases	false
New resource unit	new cbr2019.Truck()
Speed	30
Home location is	self.HOME_SINGLE_NODE
Home location (nodes)	{}
'End of shift' priority	100
'End of shift' preemption policy	self.PP_NO_PREEMPTION
'End of shift' may preempt	true
Breaks	false
Failures / repairs	false
Maintenance	false
Custom tasks	false
Add units to:	true
Population	main.trucks
Force statistics collection	true

ResourceTaskStart: resourceTaskStart

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Truck]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Truck]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	

null	null
Show at runtime	true
Public	false
Logging	true

null	null
Start here:	true

Delay: ReadyToGo

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Type	self.TIMEOUT
Delay time	uniform(3, 5)
Maximum capacity	true
Forced pushing	false
Restore agent location on exit	true
Force statistics collection	false

MoveTo: toDebris

nullagent.client

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	

null	null
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true
Description	
Description	agent.client

null	null
Agent	self.MODE_MOVE_TO
Destination:	self.DEST_AGENT
Agent	agent.client
... with offset	false
Straight movement	false
Movement is defined by:	self.MOVE_SPEED
Set agent's speed	false

Delay: LoadingDebris

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Type	self.TIMEOUT
Delay time	triangular(0.2, 0.5, 0.6)
Maximum capacity	true
Forced pushing	false
Restore agent location on exit	true
Force statistics collection	false

null	null
On at exit	//send("Delivered!",agent.customer); //send ("PickedUp", agent.customer);

MoveTo: moveToTDMS

nullDestination : Agent/unit
Agent : main.tDMS

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Truck]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Truck]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true
Description	
Description	Destination : Agent/unit Agent : main.tDMS

null	null
Agent	self.MODE_MOVE_TO
Destination:	self.DEST_AGENT
Agent	main.tDMS
... with offset	false
Straight movement	false
Movement is defined by:	self.MOVE_SPEED
Set agent's speed	false

ResourceTaskEnd: resourceTaskEnd

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Truck]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Truck]
Show name	true

null	null
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Move resource to its home location	true
Release resources seized by this unit	true

Source: source

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Arrivals defined by	self.MANUAL
New agent	new Agent()
Location of arrival	self.LOCATION_NOT_SPECIFIED
Add agents to:	false
Forced pushing	true

Queue: WaitingChipping

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]

null	null
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Maximum capacity	true
Queuing	self.QUEUING_FIFO
Enable exit on timeout	false
Enable preemption	false
Restore agent location on exit	true
Force statistics collection	false

Delay: UnloadingAtTDMS

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Type	self.TIMEOUT
Delay time	triangular(5, 10, 15)
Capacity	main.TdmsNumLoaders
Maximum capacity	false
Forced pushing	false

null	null
Restore agent location on exit	true
Force statistics collection	false
On exit	source.inject(1);

Queue: NoProcessing

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Maximum capacity	true
Queuing	self.QUEUING_FIFO
Enable exit on timeout	false
Enable preemption	false
Restore agent location on exit	true
Force statistics collection	false

SelectOutput5: selectOutput5

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location

null	null
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Use:	self.TYPE_PROBABILITIES
Probability 1	2
Probability 2	7
Probability 3	1
Probability 4	0
Probability 5	0

Sink: sink1

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
On enter	main.source.inject(1);
Destroy policy:	com.anylogic.libraries.processmodeling.Sink.DESTROY_ONLY_CREATED_IN_SOURCE

Sink: sink2

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]

null	null
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
On enter	main.source.inject(1); //main.source1.inject(1);
Destroy policy:	com.anylogic.libraries.processmodeling.Sink.DESTROY_ONLY_CREATED_IN_SOURCE

Sink: sink

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Destroy policy:	com.anylogic.libraries.processmodeling.Sink.DESTROY_ONLY_CREATED_IN_SOURCE

Release: release

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false

null	null
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Release	self.ALL
Moving resources	true
Wrap-up (e.g. move home)	self.WRAP_UP_ALWAYS
'Wrap-up' usage statistics are:	self.USAGE_BUSY

Queue: WaitingAtTDMS

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Capacity	main.TdmsTruckCap
Maximum capacity	false
Queuing	self.QUEUING_FIFO
Enable exit on timeout	false
Enable preemption	false
Restore agent location on exit	true
Force statistics collection	false

Delay: Processing

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Type	self.TIMEOUT
Delay time	triangular(4, 5, 6)
Capacity	main.NumChipper
Maximum capacity	false
Forced pushing	false
Restore agent location on exit	true
Force statistics collection	false

TimeMeasureStart: timeMeasureStart

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

TimeMeasureEnd: timeMeasureEnd

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
TimeMeasureStart blocks	{ timeMeasureStart }
Dataset capacity	100

TimeMeasureStart: timeMeasureStart1

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

TimeMeasureEnd: timeMeasureEnd1

null	null
General	
Population of agents	false

null	null
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
TimeMeasureStart blocks	{ timeMeasureStart1 }
Dataset capacity	500

Queue: RecycableMaterials

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Maximum capacity	true
Queuing	self.QUEUING_FIFO
Enable exit on timeout	false
Enable preemption	false
Restore agent location on exit	true
Force statistics collection	false

Sink: sink3

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Destroy policy:	com.anylogic.libraries.processmodeling.Sink.DESTROY_ONLY_CREATED_IN_SOURCE

Delay: PickByRecycling

null	null
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Movement	
Initial Speed Code	(10 : MPS)
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

null	null
Type	self.TIMEOUT
Delay time	triangular(0.5, 1, 1.5)
Capacity	1
Maximum capacity	false
Forced pushing	false

null	null
Restore agent location on exit	true
Force statistics collection	false

Time Plot: chart

null	null
General	
Public	false
Data update	
Analysis auto update	true
ANALYSIS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Dataset Samples To Keep	100
Scale	
Time window	100
Time	model time units
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Label format	Model time units
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	true
Fill area under line	false
Interpolation	Linear
Position and size	
x	90.0
Width	260.0
y	610.0
Height	210.0
Legend	
Show legend	true
Legend size	30.0
Legend text color	black
Chart area	
Chart Area: X Offset	50.0
Chart Area: Width	180.0
Chart Area: Y Offset	30.0
Chart Area: Height	120.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Time window moves	Continuously

null	null
Show name	false
Logging	true

null	null	null	null	null	null	null	null
Dataset Title	value	WaitingChipping.size()	NONE	darkOrange	true	1.0	LINEAR

Histogram: chart1

null	null
General	
Show mean	true
Show CDF	false
Show PDF	true
Public	true
Data update	
Analysis auto update	false
Appearance	
Bars relative width	0.8
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Position and size	
x	830.0
Width	260.0
y	260.0
Height	210.0
Legend	
Show legend	true
Legend size	30.0
Legend text color	black
Chart area	
Chart Area: X Offset	50.0
Chart Area: Width	180.0
Chart Area: Y Offset	30.0
Chart Area: Height	120.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false

null	null	null	null	null	null	null	null
TruckWaitingTimeAt TDMS	timeMeasureEnd.distribution	coral	darkOrange	dodgerBlue	1	coral	gold

Histogram: chart2

null	null
General	
Show mean	true
Show CDF	false
Show PDF	true
Public	true
Data update	
Analysis auto update	false
Appearance	
Bars relative width	0.8
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Position and size	
x	580.0
Width	260.0
y	260.0
Height	210.0
Legend	
Show legend	true
Legend size	30.0
Legend text color	black
Chart area	
Chart Area: X Offset	50.0
Chart Area: Width	180.0
Chart Area: Y Offset	30.0
Chart Area: Height	120.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false

null	null	null	null	null	null	null	null
DebrisWaitingTimeOnSite	timeMeasureEnd1.distribution	gold	goldenRod	yellowGreen	1	goldenRod	crimson

Statistics: WaitingTrucksAtTDMS

null	null
General	
Statistics value	WaitingAtTDMS.size() //WaitingAtTDMS.in.count()-WaitingAtTDMS.out.count()
Discrete	true
Show at runtime	true

null	null
Data update	
Analysis auto update	true
ANALYSIS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Logging	true

3D Object: warehouse_3

null	null
General	
Scale	1.25
Auto scale	true
File Name	x3d/warehouse_3.x3d
Show at runtime	true
Lock	false
Public	true
Position and size	
x	0.0
y	0.0
z	0.0
Rotation	0.0
Advanced	
Show in	2D and 3D
Enable AnyLogic light shaders	true
Show name	false

View Area: viewTDMS

null	null
General	
Title	viewTDMS
Show name	false
Position and size	
x	0.0
Width	1380.0
y	0.0
Height	800.0

Link to agents: connections

null	null
General	
Show at runtime	true
Show name	true
Communication	

null	null
Message type	Order
On receive	enter.take(msg); // place a received order massage into the enter block
Animation	
Draw line	false

Agent Type: Truck

null	null
Agent in flowcharts	
Use in flowcharts as	Agent
Movement	
Speed	(10 : MPS)
Rotate animation towards movement	true
Rotate vertically as well (along Z-axis)	false
Space and network	
Space Type	Continuous
Advanced Java	
Generic	false
Advanced	
Logging	true
Auto-create datasets	true
AOC_DATASETS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Limit the number of data samples	false

main

connections

client

Scale: scale

null	null
General	
Unit	meter
Scale	10.0
Type	Defined graphically
Length, pixels	100.0
Show at runtime	false
Lock	false
Public	false

null	null
Position and size	
x	0.0
y	-150.0
Rotation	0.0

Parameter: client

null	null
General	
Array	false
Type	Debris
Show at runtime	false
Show name	true
Value editor	
Editor control	Text
Advanced	
System dynamics units	false
Save in snapshot	true

3D Object: tip_truck

null	null
General	
Scale	0.5
Auto scale	true
File Name	x3d/tip_truck.x3d
Show at runtime	true
Lock	false
Public	true
Position and size	
x	0.0
y	0.0
z	0.0
Rotation	0.0
Advanced	
Show in	2D and 3D
Enable AnyLogic light shaders	true
Show name	false

Link to agents: connections

null	null
General	

null	null
Show at runtime	true
Show name	true
Communication	
Message type	Object
Animation	
Draw line	false

Agent Type: Order

null	null
Agent in flowcharts	
Use in flowcharts as	Agent
Movement	
Speed	(10 : MPS)
Rotate animation towards movement	true
Rotate vertically as well (along Z-axis)	false
Space and network	
Space Type	Continuous
Advanced Java	
Generic	false
Advanced	
Logging	true
Auto-create datasets	true
AOC_DATASETS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Limit the number of data samples	false

main

connections

customer

Scale: scale

null	null
General	
Unit	meter
Scale	10.0
Type	Defined graphically
Length, pixels	100.0
Show at runtime	false
Lock	false

null	null
Public	false
Position and size	
x	0.0
y	-150.0
Rotation	0.0

Parameter: customer

null	null
General	
Array	false
Type	Debris
Show at runtime	true
Show name	true
Value editor	
Label	customer
Editor control	Text
Advanced	
System dynamics units	false
Save in snapshot	true

Link to agents: connections

null	null
General	
Show at runtime	true
Show name	true
Communication	
Message type	Object
Animation	
Draw line	false

Agent Type: Ltrucks

null	null
Agent in flowcharts	
Use in flowcharts as	Agent
Movement	
Speed	(10 : MPS)
Rotate animation towards movement	true
Rotate vertically as well (along Z-axis)	false
Space and network	
Space Type	Continuous
Advanced Java	
Generic	false
Advanced	

null	null
Logging	true
Auto-create datasets	true
AOC_DATASETS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Limit the number of data samples	false

main

connections

Scale: scale

null	null
General	
Unit	meter
Scale	10.0
Type	Defined graphically
Length, pixels	100.0
Show at runtime	false
Lock	false
Public	false
Position and size	
x	0.0
y	-150.0
Rotation	0.0

3D Object: truck

null	null
General	
Scale	0.3
Auto scale	true
File Name	x3d/truck.x3d
Show at runtime	true
Lock	false
Public	true
Position and size	
x	0.0
y	0.0
z	0.0
Rotation	0.0
Advanced	

null	null
Show in	2D and 3D
Enable AnyLogic light shaders	true
Show name	false

Link to agents: connections

null	null
General	
Show at runtime	true
Show name	true
Communication	
Message type	Object
Animation	
Draw line	false

Simulation Experiment: Simulation

null	null
General	
Maximum available memory	8192
Agent type	main
Model time	
Execution mode	Real time with scale
Real time scale	1.0
Stop option	Stop at specified date
Initial time	0.0
Initial date	Wed Aug 10 00:00:00 GMT 2016
Final date	Tue Nov 08 00:00:00 GMT 2016
Randomness	
Random Number Generation Type	Fixed seed (reproducible simulation runs)
Seed value	1
Selection mode for simultaneous events	LIFO (in the reverse order of scheduling)
Window	
Title	20170513_louisiana : Simulation
Enable zoom and panning	true
Maximized size	false
Close confirmation	false
Advanced	
Enable Antialiasing	true
Enable Enhanced Model Elements Animation	true
Adaptive frame management	true
CPU time balance	1 : 2
Load root from snapshot	false

Disaster Debris Management - System behaviors

Run

Text: text

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	Disaster Debris Management - System behaviors
Appearance	
Color	royalBlue
Alignment	LEFT
Position and size	
x	40.0
y	30.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Button: button

null	null
General	
Enabled	true
Dynamic: Label	getState() == IDLE ? "Run" : "Top level agent"
Label text	Run
Action	
Action	if (getState() == IDLE) run(); getPresentation().setPresentable(getEngine().getRoot());
Position and size	
x	40.0
Width	100.0
y	80.0
Height	30.0
Advanced	
Show name	false

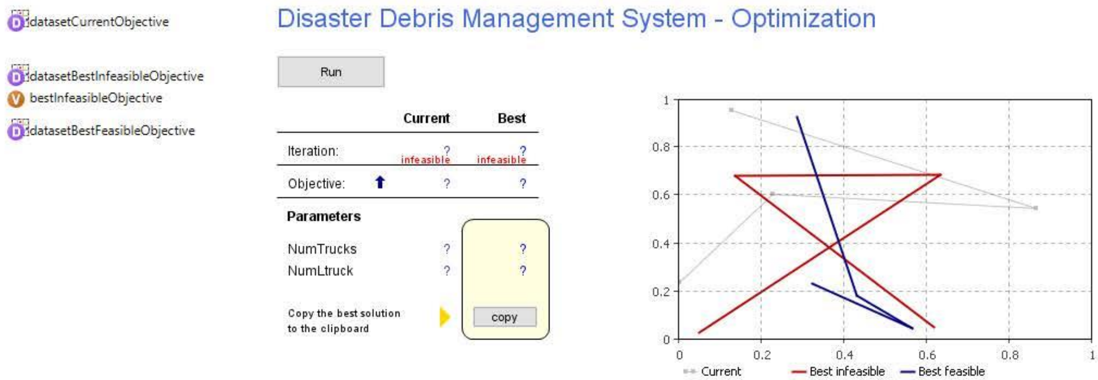
Optimization Experiment: Optimization

null	null
General	

null	null
Maximum available memory	16384
Automatic stop	false
Iteration count	500
Stop After Iteration Count	true
Objective function code	root.Completed //root.tDMS.trucks.utilization() + root.LtruckPool.utilization()
Objective	maximize
Agent type	main
Model time	
Stop option	Stop at specified date
Initial time	0.0
Initial date	Wed Aug 10 00:00:00 GMT 2016
Final date	Tue Nov 08 00:00:00 GMT 2016
Randomness	
Random Number Generation Type	Fixed seed (reproducible simulation runs)
Seed value	1
Selection mode for simultaneous events	LIFO (in the reverse order of scheduling)
Replications	
Use replications	false
Window	
Title	Equipment Utilization opt.
Enable zoom and panning	true
Maximized size	false
Close confirmation	false
Java actions	
Before each experiment run	datasetCurrentObjective.reset(); datasetBestInfeasibleObjective.reset(); datasetBestFeasibleObjective.reset();
After iteration code	if (isBestSolutionFeasible()) { datasetBestFeasibleObjective.update(); } if (!isCurrentSolutionFeasible()) { bestInfeasibleObjective = max(bestInfeasibleObjective, getCurrentObjectiveValue()); } if (bestInfeasibleObjective != Double.NEGATIVE_INFINITY) { datasetBestInfeasibleObjective.update(); }
Advanced	
Allow parallel evaluations	true
Load root from snapshot	false

		null			
null	null	null	null	null	null
NumTrucks	INTEGER	100	200	1	150
NumLtruck	INTEGER	3	6	1	4
TdmsTruckCap	FIXED	100			

null	null	null			
		null	null	null	null
TdmsNumLoaders	FIXED				
DebrisAtUnit	FIXED				
NumChipper	FIXED				



Variable: bestInfeasibleObjective

null	null
General	
Initial value	Double.NEGATIVE_INFINITY
Type	double
Show at runtime	true
Show name	true
Advanced	
Access type	public
Static	false
Constant	false
Save in snapshot	true
System dynamics units	false

Plot: plotObjective

null	null
Data update	
Analysis auto update	false
Dataset Samples To Keep	100
Scale	
Horizontal scale	Auto

null	null
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	true
Interpolation	Linear
Position and size	
x	330.0
Width	480.0
y	100.0
Height	300.0
Legend	
Show legend	true
Legend size	40.0
Legend text color	black
Chart area	
Chart Area: X Offset	80.0
Chart Area: Width	380.0
Chart Area: Y Offset	20.0
Chart Area: Height	220.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false
Logging	true

		null						
null	null	null	null	null	null	null	null	null
Current	dataset	datasetCurrentObjective		SQUARE	silver	true	1.0	LINEAR
Best infeasible	dataset	datasetBestInfeasibleObjective		NONE	new Color(192, 0, 0)	true	2.0	LINEAR
Best feasible	dataset	datasetBestFeasibleObjective		NONE	navy	true	2.0	LINEAR

Data Set: datasetCurrentObjective

null	null
General	
Dataset Samples To Keep	500
Axis Data Vertical Y Axis	getCurrentObjectiveValue()
Axis Data Freeze X Axis	true
Show at runtime	false
Show name	true
Data update	

null	null
Analysis auto update	true
Logging	true

Data Set: datasetBestInfeasibleObjective

null	null
General	
Dataset Samples To Keep	500
Axis Data Vertical Y Axis	bestInfeasibleObjective
Axis Data Freeze X Axis	true
Show at runtime	false
Show name	true
Data update	
Analysis auto update	false
Logging	true

Data Set: datasetBestFeasibleObjective

null	null
General	
Dataset Samples To Keep	500
Axis Data Vertical Y Axis	getBestObjectiveValue()
Axis Data Freeze X Axis	true
Show at runtime	false
Show name	true
Data update	
Analysis auto update	false
Logging	true

Text: text

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	Disaster Debris Management System - Optimization
Appearance	
Color	royalBlue
Alignment	LEFT
Position and size	
x	40.0
y	30.0
z	0.0
Rotation	0.0
Advanced	

null	null
Show name	false

Text: text1

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	Current
Appearance	
Color	black
Alignment	RIGHT
Position and size	
x	200.0
y	130.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text2

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	Best
Appearance	
Color	black
Alignment	RIGHT
Position and size	
x	270.0
y	130.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Line: line

null	null
General	
Show at runtime	true
Lock	false

null	null
Appearance	
Line color	black
Line width	1.0
Line style	SOLID
Position and size	
x	40.0
dX	240.0
y	150.0
dY	0.0
z	0.0
dZ	0.0
Z-Height	10.0
Advanced	
Show name	false

Text: text3

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	Iteration:
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	50.0
y	160.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text4

null	null
General	
Dynamic: Visible	getCurrentIteration() > 0
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(getCurrentIteration())
Appearance	

null	null
Color	darkSlateBlue
Alignment	RIGHT
Position and size	
x	200.0
y	160.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text5

null	null
General	
Dynamic: Visible	getCurrentIteration() > 0 && !isCurrentSolutionFeasible()
Show at runtime	true
Lock	false
Text	
Text	infeasible
Appearance	
Color	red
Alignment	RIGHT
Position and size	
x	200.0
y	169.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text6

null	null
General	
Dynamic: Visible	getBestIteration() > 0
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(getBestIteration())
Appearance	
Color	blue
Alignment	RIGHT
Position and size	
x	270.0

null	null
y	160.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text7

null	null
General	
Dynamic: Visible	getBestIteration() > 0 && !isBestSolutionFeasible()
Show at runtime	true
Lock	false
Text	
Text	infeasible
Appearance	
Color	red
Alignment	RIGHT
Position and size	
x	270.0
y	169.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Line: line1

null	null
General	
Show at runtime	true
Lock	false
Appearance	
Line color	black
Line width	1.0
Line style	SOLID
Position and size	
x	40.0
dX	240.0
y	180.0
dY	0.0
z	0.0
dZ	0.0
Z-Height	10.0
Advanced	

null	null
Show name	false

Text: text8

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	Objective:
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	50.0
y	190.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text9

null	null
General	
Dynamic: Visible	getCurrentIteration() > 0
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(getCurrentObjectiveValue())
Appearance	
Color	darkSlateBlue
Alignment	RIGHT
Position and size	
x	200.0
y	190.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text10

null	null
General	

null	null
Dynamic: Visible	getBestIteration() > 0
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(getBestObjectiveValue())
Appearance	
Color	blue
Alignment	RIGHT
Position and size	
x	270.0
y	190.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Line: line2

null	null
General	
Show at runtime	true
Lock	false
Appearance	
Line color	black
Line width	1.0
Line style	SOLID
Position and size	
x	40.0
dX	240.0
y	210.0
dY	0.0
z	0.0
dZ	0.0
Z-Height	10.0
Advanced	
Show name	false

Polyline: polyline

null	null
General	
Polyline closed	true
Show at runtime	true
Lock	false

null	null
Appearance	
Fill color	darkBlue
Line width	1.0
Line style	SOLID
Position and size	
x	133.0
y	202.0
z	0.0
Z-Height	10.0
Advanced	
Show name	false

Text: text11

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	Parameters
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	50.0
y	220.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Rounded Rectangle: roundRect

null	null
General	
Show at runtime	true
Lock	false
Appearance	
Fill color	lightYellow
Line color	black
Line width	1.0
Line style	SOLID
Position and size	
x	210.0
Width	80.0

null	null
y	230.0
Height	110.0
Rotation	0.0
Radius	10.0
Advanced	
Show name	false

Text: text12

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	NumTrucks
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	50.0
y	250.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text13

null	null
General	
Dynamic: Visible	getCurrentIteration() > 0
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(NumTrucks)
Appearance	
Color	darkSlateBlue
Alignment	RIGHT
Position and size	
x	200.0
y	250.0
z	0.0
Rotation	0.0
Advanced	

null	null
Show name	false

Text: text14

null	null
General	
Dynamic: Visible	getBestIteration() > 0
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(getBestParamValue(_oqvar_NumTrucks))
Appearance	
Color	blue
Alignment	RIGHT
Position and size	
x	270.0
y	250.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text15

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	NumLtruck
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	50.0
y	270.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text16

null	null
General	

null	null
Dynamic: Visible	getCurrentIteration() > 0
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(NumLtruck)
Appearance	
Color	darkSlateBlue
Alignment	RIGHT
Position and size	
x	200.0
y	270.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text17

null	null
General	
Dynamic: Visible	getBestIteration() > 0
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(getBestParamValue(_oqvar_NumLtruck))
Appearance	
Color	blue
Alignment	RIGHT
Position and size	
x	270.0
y	270.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text18

null	null
General	
Show at runtime	true
Lock	false
Text	

null	null
Text	Copy the best solution to the clipboard
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	50.0
y	310.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Polyline: polyline1

null	null
General	
Polyline closed	true
Show at runtime	true
Lock	false
Appearance	
Fill color	gold
Line width	1.0
Line style	SOLID
Position and size	
x	190.0
y	310.0
z	0.0
Z-Height	10.0
Advanced	
Show name	false

Button: button

null	null
General	
Dynamic: Enable	getState() == IDLE
Enabled	true
Label text	Run
Action	
Action	run();
Position and size	
x	40.0
Width	100.0
y	80.0

null	null
Height	30.0
Advanced	
Show name	false

Button: button1

null	null
General	
Dynamic: Enable	getBestIteration() > 0
Enabled	true
Label text	copy
Action	
Action	String s = ""; s += "NumTrucks\t" + format(getBestParamValue(_oqvar_NumTrucks)) + "\n"; s += "NumLtruck\t" + format(getBestParamValue(_oqvar_NumLtruck)) + "\n"; copyToClipboard(s);
Position and size	
x	220.0
Width	60.0
y	310.0
Height	20.0
Advanced	
Show name	false

Parameter Variation Experiment: SensitivityAnalysis

null	null
General	
Maximum available memory	4096
Agent type	main
Model time	
Stop option	Stop at specified date
Initial time	0.0
Initial date	Wed Aug 10 00:00:00 GMT 2016
Final date	Tue Nov 08 00:00:00 GMT 2016
Randomness	
Random Number Generation Type	Fixed seed (reproducible simulation runs)
Seed value	1
Selection mode for simultaneous events	LIFO (in the reverse order of scheduling)
Replications	
Use replications	false
Window	
Title	LT1verFinal3 : SensitivityAnalysis
Enable zoom and panning	true
Maximized size	false

null	null
Close confirmation	false
Java actions	
Before each experiment run	chart0.removeAll();
After simulation run	Color color = lerpColor((getCurrentIteration() - 1) / (double) (getMaximumIterations() - 1), blue, red); chart0.addDataSet(root.DebrisAtTDMSdata, format(root.NumTrucks), color, true, Chart.INTERPOLATION_LINEAR, 1, Chart.POINT_NONE);
Advanced	
Allow parallel evaluations	true
Load root from snapshot	false

		null		
null	null	null	null	null
NumTrucks	RANGE	50	100	1
NumLtruck	FIXED	3		
TdmsTruckCap	FIXED	100		
TdmsNumLoaders	FIXED	2		
DebrisAtUnit	FIXED	50		
NumChipper	FIXED	1		

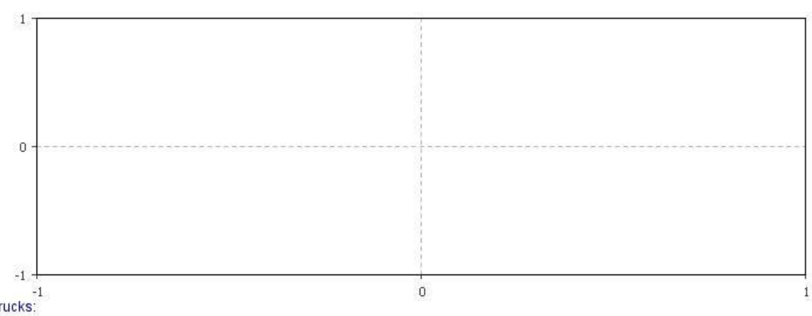
LT1verFinal3 : SensitivityAnalysis

Run

Varied Parameter

NumTrucks ? Number of runs: ?

Charts



Plot: chart0

null	null

null	null
Data update	
Analysis auto update	false
Dataset Samples To Keep	100
Scale	
Horizontal scale	Auto
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	false
Position and size	
x	40.0
Width	760.0
y	180.0
Height	300.0
Legend	
Show legend	true
Legend size	40.0
Legend text color	black
Chart area	
Chart Area: X Offset	80.0
Chart Area: Width	660.0
Chart Area: Y Offset	20.0
Chart Area: Height	220.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false
Logging	true

Text: text

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	LT1verFinal3 : SensitivityAnalysis
Appearance	
Color	royalBlue
Alignment	LEFT
Position and size	
x	40.0

null	null
y	30.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text1

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	Varied Parameter
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	40.0
y	120.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Line: line

null	null
General	
Show at runtime	true
Lock	false
Appearance	
Line color	black
Line width	1.0
Line style	SOLID
Position and size	
x	150.0
dX	650.0
y	130.0
dY	0.0
z	0.0
dZ	0.0
Z-Height	10.0
Advanced	
Show name	false

Text: text2

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	NumTrucks
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	40.0
y	140.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text3

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(NumTrucks)
Appearance	
Color	darkSlateBlue
Alignment	RIGHT
Position and size	
x	260.0
y	140.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text4

null	null
General	
Show at runtime	true
Lock	false
Text	

null	null
Text	Number of runs:
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	420.0
y	140.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text5

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(getEngine().getRunCount())
Appearance	
Color	darkSlateBlue
Alignment	RIGHT
Position and size	
x	640.0
y	140.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text6

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	Charts
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	40.0

null	null
y	160.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Line: line1

null	null
General	
Show at runtime	true
Lock	false
Appearance	
Line color	black
Line width	1.0
Line style	SOLID
Position and size	
x	90.0
dX	710.0
y	170.0
dY	0.0
z	0.0
dZ	0.0
Z-Height	10.0
Advanced	
Show name	false

Text: text7

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	NumTrucks:
Appearance	
Color	darkBlue
Alignment	RIGHT
Position and size	
x	120.0
y	440.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Button: button

null	null
General	
Dynamic: Enable	getState() == IDLE
Enabled	true
Label text	Run
Action	
Action	run();
Position and size	
x	40.0
Width	100.0
y	80.0
Height	30.0
Advanced	
Show name	false

Parameter Variation Experiment: MonteCarlo

null	null
General	
Maximum available memory	4096
Agent type	main
Model time	
Stop option	Stop at specified date
Initial time	0.0
Initial date	Wed Aug 10 00:00:00 GMT 2016
Final date	Tue Nov 08 00:00:00 GMT 2016
Randomness	
Random Number Generation Type	Random seed (unique simulation runs)
Selection mode for simultaneous events	LIFO (in the reverse order of scheduling)
Replications	
Use replications	false
Window	
Title	LT1verFinal3 : MonteCarlo
Enable zoom and panning	true
Maximized size	false
Close confirmation	false
Java actions	
After simulation run	histogram0_data.add(root.Completed);
Advanced	
Allow parallel evaluations	true
Load root from snapshot	false

null	null	null		
		null	null	null
NumTrucks	RANGE	60	100	1
NumLtruck	FIXED	2		
TdmsTruckCap	FIXED	150		
TdmsNumLoaders	RANGE	1	5	1
DebrisAtUnit	FIXED	50		
NumChipper	FIXED	2		

LT1verFinal3 : MonteCarlo

Run

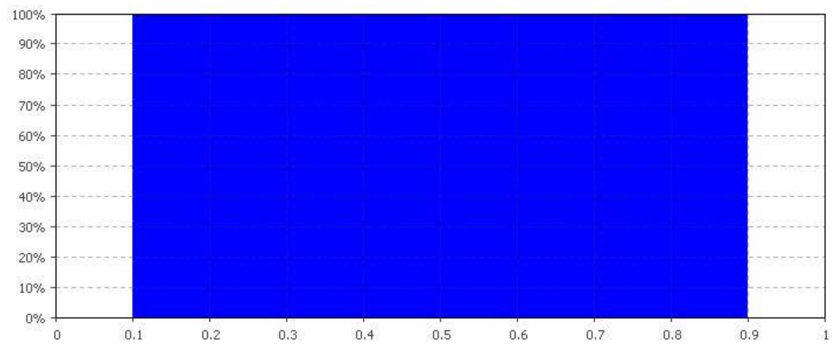
Number of runs: ?

Varied Parameters

NumTrucks ?
NumLtruck ?
TdmsTruckCap ?
TdmsNumLoaders ?
DebrisAtUnit ?
NumChipper ?

Charts

histogram0_data



Histogram: histogram0

null	null
General	
Show mean	false
Show CDF	false
Show PDF	true
Data update	
Analysis auto update	false
Appearance	
Bars relative width	0.8

null	null
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Position and size	
x	40.0
Width	760.0
y	280.0
Height	300.0
Legend	
Show legend	false
Chart area	
Chart Area: X Offset	80.0
Chart Area: Width	660.0
Chart Area: Y Offset	20.0
Chart Area: Height	260.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false

null	null	null	null	null	null	null	null
	histogram0_data	blue	black	saddleBrown	1	navy	cyan

Histogram Data: histogram0_data

null	null
General	
Logging	true
Calculate percentilies	false
Calculate CDF	true
Number of intervals	1
Show at runtime	false
Show name	true
Values range	
Data range	true
Initial interval size	1
Data update	
Analysis auto update	false

Text: text

null	null
General	
Show at runtime	true
Lock	false

null	null
Text	
Text	LT1verFinal3 : MonteCarlo
Appearance	
Color	royalBlue
Alignment	LEFT
Position and size	
x	40.0
y	30.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text1

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	Number of runs:
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	400.0
y	90.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text2

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(getEngine().getRunCount())
Appearance	
Color	darkSlateBlue
Alignment	RIGHT
Position and size	

null	null
x	620.0
y	90.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text3

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	Varied Parameters
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	40.0
y	120.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Line: line

null	null
General	
Show at runtime	true
Lock	false
Appearance	
Line color	black
Line width	1.0
Line style	SOLID
Position and size	
x	150.0
dX	650.0
y	130.0
dY	0.0
z	0.0
dZ	0.0
Z-Height	10.0
Advanced	

null	null
Show name	false

Text: text4

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	NumTrucks
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	40.0
y	140.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text5

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(NumTrucks)
Appearance	
Color	darkSlateBlue
Alignment	RIGHT
Position and size	
x	260.0
y	140.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text6

null	null
General	
Show at runtime	true

null	null
Lock	false
Text	
Text	NumLtruck
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	40.0
y	160.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text7

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(NumLtruck)
Appearance	
Color	darkSlateBlue
Alignment	RIGHT
Position and size	
x	260.0
y	160.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text8

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	TdmsTruckCap
Appearance	
Color	black
Alignment	LEFT

null	null
Position and size	
x	40.0
y	180.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text9

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(TdmsTruckCap)
Appearance	
Color	darkSlateBlue
Alignment	RIGHT
Position and size	
x	260.0
y	180.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text10

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	TdmsNumLoaders
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	40.0
y	200.0
z	0.0
Rotation	0.0
Advanced	

null	null
Show name	false

Text: text11

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(TdmsNumLoaders)
Appearance	
Color	darkSlateBlue
Alignment	RIGHT
Position and size	
x	260.0
y	200.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text12

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	DebrisAtUnit
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	40.0
y	220.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text13

null	null
General	
Show at runtime	true

null	null
Lock	false
Text	
Text	?
Dynamic: Text	format(DebrisAtUnit)
Appearance	
Color	darkSlateBlue
Alignment	RIGHT
Position and size	
x	260.0
y	220.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text14

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	NumChipper
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	40.0
y	240.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text15

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(NumChipper)
Appearance	
Color	darkSlateBlue

null	null
Alignment	RIGHT
Position and size	
x	260.0
y	240.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text16

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	Charts
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	40.0
y	260.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Line: line1

null	null
General	
Show at runtime	true
Lock	false
Appearance	
Line color	black
Line width	1.0
Line style	SOLID
Position and size	
x	90.0
dX	710.0
y	270.0
dY	0.0
z	0.0
dZ	0.0

null	null
Z-Height	10.0
Advanced	
Show name	false

Button: button

null	null
General	
Dynamic: Enable	getState() == IDLE
Enabled	true
Label text	Run
Action	
Action	run();
Position and size	
x	40.0
Width	100.0
y	80.0
Height	30.0
Advanced	
Show name	false

Parameter Variation Experiment: SensitivityAnalysis1

null	null
General	
Maximum available memory	16384
Agent type	main
Model time	
Stop option	Stop at specified date
Initial time	0.0
Initial date	Wed Aug 10 00:00:00 GMT 2016
Final date	Tue Nov 08 00:00:00 GMT 2016
Randomness	
Random Number Generation Type	Random seed (unique simulation runs)
Selection mode for simultaneous events	LIFO (in the reverse order of scheduling)
Replications	
Use replications	false
Window	
Title	Sensitivity Analysis
Enable zoom and panning	true
Maximized size	false
Close confirmation	false
Java actions	
Before each experiment run	chart0.removeAll(); chart1.removeAll(); chart2_dataSet.reset();

null	null
	chart3_dataSet.reset(); chart4_dataSet.reset(); chart5_dataSet.reset(); //chart6_dataSet.reset();
After simulation run	Color color = lerpColor((getCurrentIteration() - 1) / (double) (getMaximumIterations() - 1), blue, red); chart0.addDataSet(root.DebrisAtTDMSdata, format(root.NumTrucks), color, true, Chart.INTERPOLATION_LINEAR, 1, Chart.POINT_NONE); chart1.addDataSet(root.DebrisatLandfill, format(root.NumTrucks), color, true, Chart.INTERPOLATION_LINEAR, 1, Chart.POINT_NONE); chart6.addDataSet(root.CompletedDS, format(root.NumTrucks), color, true, Chart.INTERPOLATION_LINEAR, 1, Chart.POINT_NONE); chart2_dataSet.add(root.NumTrucks, root.DebrisAtLandfill30days); chart3_dataSet.add(root.NumTrucks, root.DebrisAtLandfill60days); chart4_dataSet.add(root.NumTrucks, root.DebrisAtLandfill90days); chart5_dataSet.add(root.NumTrucks, root.Completed); //chart6_dataSet.add(root.NumTrucks, root.CompletedDS);
Advanced	
Allow parallel evaluations	true
Load root from snapshot	false

		null		
null	null	null	null	null
NumTrucks	RANGE	160	240	10
NumLtruck	FIXED	6		
TdmsTruckCap	FIXED	200		
TdmsNumLoaders	FIXED	4		
DebrisAtUnit	FIXED	800		
NumChipper	FIXED	2		

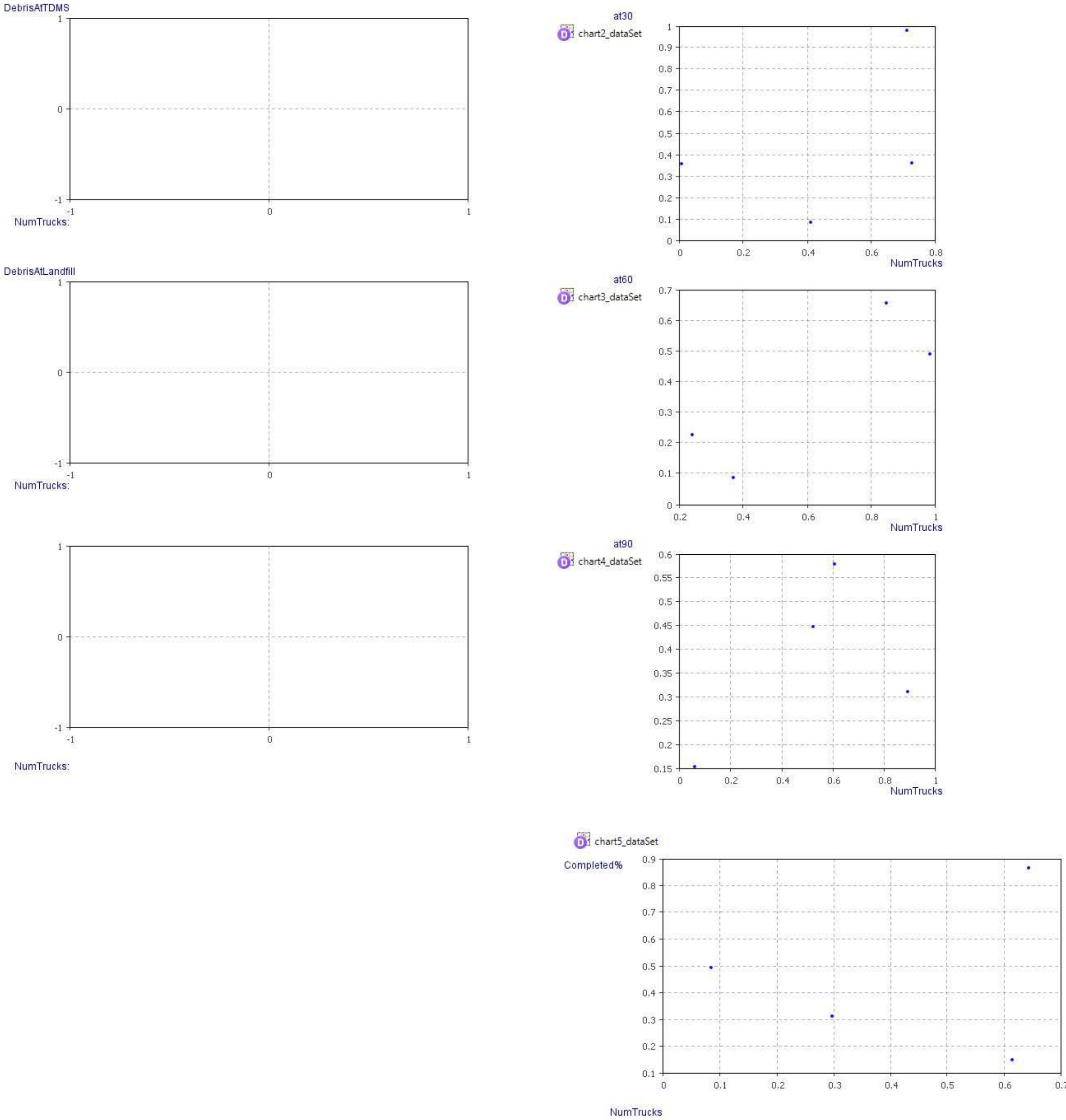
System Sensitivity Analysis

Run

Varied Parameter

NumTrucks ? Number of runs: ?

Charts



Plot: chart0

null	null
Data update	
Analysis auto update	false
Dataset Samples To Keep	100
Scale	
Horizontal scale	Auto
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	false
Position and size	
x	40.0
Width	582.624
y	180.0
Height	300.0
Legend	
Show legend	true
Legend size	40.0
Legend text color	black
Chart area	
Chart Area: X Offset	80.0
Chart Area: Width	482.624
Chart Area: Y Offset	20.0
Chart Area: Height	220.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false
Logging	true

Plot: chart1

null	null
Data update	
Analysis auto update	false
Dataset Samples To Keep	100
Scale	
Horizontal scale	Auto
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT

null	null
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	false
Position and size	
x	40.0
Width	582.624
y	500.0
Height	300.0
Legend	
Show legend	true
Legend size	40.0
Legend text color	black
Chart area	
Chart Area: X Offset	80.0
Chart Area: Width	482.624
Chart Area: Y Offset	20.0
Chart Area: Height	220.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false
Logging	true

Plot: chart2

null	null
Data update	
Analysis auto update	false
Dataset Samples To Keep	100
Scale	
Horizontal scale	Auto
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	false
Position and size	
x	780.0
Width	410.0
y	190.0
Height	300.0
Legend	

null	null
Show legend	false
Chart area	
Chart Area: X Offset	80.0
Chart Area: Width	310.0
Chart Area: Y Offset	20.0
Chart Area: Height	260.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false
Logging	true

		null						
null	null	null	null	null	null	null	null	null
at30	dataset	chart2_dataSet		CIRCLE	blue	false	1.0	LINEAR

Plot: chart3

null	null
Data update	
Analysis auto update	false
Dataset Samples To Keep	100
Scale	
Horizontal scale	Auto
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	false
Position and size	
x	780.0
Width	410.0
y	510.0
Height	300.0
Legend	
Show legend	false
Chart area	
Chart Area: X Offset	80.0
Chart Area: Width	310.0
Chart Area: Y Offset	20.0
Chart Area: Height	260.0
Chart Area: Background Color	white

null	null
Chart area border color	black
Advanced	
Show name	false
Logging	true

null	null	null		null	null	null	null	null
		null	null					
at60	dataset	chart3_dataSet		CIRCLE	blue	false	1.0	LINEAR

Plot: chart4

null	null
Data update	
Analysis auto update	false
Dataset Samples To Keep	100
Scale	
Horizontal scale	Auto
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	false
Position and size	
x	780.0
Width	410.0
y	830.0
Height	300.0
Legend	
Show legend	false
Chart area	
Chart Area: X Offset	80.0
Chart Area: Width	310.0
Chart Area: Y Offset	20.0
Chart Area: Height	260.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false
Logging	true

null	null	null		null	null	null	null	null
		null	null					

		null						
null	null	null	null	null	null	null	null	null
at90	dataset	chart4_dataSet		CIRCLE	blue	false	1.0	LINEAR

Plot: chart5

null	null
Data update	
Analysis auto update	false
Dataset Samples To Keep	100
Scale	
Horizontal scale	Auto
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	false
Position and size	
x	760.0
Width	582.624
y	1200.0
Height	300.0
Legend	
Show legend	false
Chart area	
Chart Area: X Offset	80.0
Chart Area: Width	482.624
Chart Area: Y Offset	20.0
Chart Area: Height	260.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false
Logging	true

		null						
null	null	null	null	null	null	null	null	null
at90	dataset	chart5_dataSet		CIRCLE	blue	false	1.0	LINEAR

Plot: chart6

null	null

null	null
Data update	
Analysis auto update	false
Dataset Samples To Keep	100
Scale	
Horizontal scale	Auto
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	false
Position and size	
x	40.0
Width	582.624
y	820.0
Height	300.0
Legend	
Show legend	true
Legend size	40.0
Legend text color	black
Chart area	
Chart Area: X Offset	80.0
Chart Area: Width	482.624
Chart Area: Y Offset	20.0
Chart Area: Height	220.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false
Logging	true

Data Set: chart2_dataSet

null	null
General	
Dataset Samples To Keep	100
Axis Data Freeze X Axis	false
Show at runtime	false
Show name	true
Data update	
Analysis auto update	false
Logging	true

Data Set: chart3_dataSet

null	null
General	
Dataset Samples To Keep	100
Axis Data Freeze X Axis	false
Show at runtime	false
Show name	true
Data update	
Analysis auto update	false
Logging	true

Data Set: chart4_dataSet

null	null
General	
Dataset Samples To Keep	100
Axis Data Freeze X Axis	false
Show at runtime	false
Show name	true
Data update	
Analysis auto update	false
Logging	true

Data Set: chart5_dataSet

null	null
General	
Dataset Samples To Keep	100
Axis Data Freeze X Axis	true
Show at runtime	false
Show name	true
Data update	
Analysis auto update	false
Logging	true

Text: text

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	System Sensitivity Analysis
Appearance	
Color	royalBlue
Alignment	LEFT
Position and size	
x	40.0

null	null
y	30.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text1

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	Varied Parameter
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	40.0
y	120.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Line: line

null	null
General	
Show at runtime	true
Lock	false
Appearance	
Line color	black
Line width	1.0
Line style	SOLID
Position and size	
x	150.0
dX	650.0
y	130.0
dY	0.0
z	0.0
dZ	0.0
Z-Height	10.0
Advanced	
Show name	false

Text: text2

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	NumTrucks
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	40.0
y	140.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text3

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(NumTrucks)
Appearance	
Color	darkSlateBlue
Alignment	RIGHT
Position and size	
x	260.0
y	140.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text4

null	null
General	
Show at runtime	true
Lock	false
Text	

null	null
Text	Number of runs:
Appearance	
Color	black
Alignment	LEFT
Position and size	
x	420.0
y	140.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text5

null	null
General	
Show at runtime	true
Lock	false
Text	
Text	?
Dynamic: Text	format(getEngine().getRunCount())
Appearance	
Color	darkSlateBlue
Alignment	RIGHT
Position and size	
x	640.0
y	140.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text6

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General	
Show at runtime	true
Lock	false
Text	
Text	Charts
Appearance	
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Position and size	
x	40.0

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y	160.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Line: line1

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General	
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Lock	false
Appearance	
Line color	black
Line width	1.0
Line style	SOLID
Position and size	
x	90.0
dX	710.0
y	170.0
dY	0.0
z	0.0
dZ	0.0
Z-Height	10.0
Advanced	
Show name	false

Text: text7

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General	
Show at runtime	true
Lock	false
Text	
Text	DebrisAtTDMS
Appearance	
Color	darkBlue
Alignment	LEFT
Position and size	
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z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text8

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General	
Show at runtime	true
Lock	false
Text	
Text	NumTrucks:
Appearance	
Color	darkBlue
Alignment	RIGHT
Position and size	
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y	440.0
z	0.0
Rotation	0.0
Advanced	
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Text: text9

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Show at runtime	true
Lock	false
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Appearance	
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Position and size	
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z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text10

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General	
Show at runtime	true
Lock	false
Text	
Text	NumTrucks:

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Appearance	
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Position and size	
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y	760.0
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Advanced	
Show name	false

Text: text11

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General	
Show at runtime	true
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Text	
Text	at30
Appearance	
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Position and size	
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Rotation	0.0
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Text: text12

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Show at runtime	true
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Text	
Text	NumTrucks
Appearance	
Color	darkBlue
Alignment	RIGHT
Position and size	
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y	490.0
z	0.0

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Rotation	0.0
Advanced	
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Text: text13

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General	
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Text	at60
Appearance	
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Alignment	LEFT
Position and size	
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z	0.0
Rotation	0.0
Advanced	
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Text: text14

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General	
Show at runtime	true
Lock	false
Text	
Text	NumTrucks
Appearance	
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Position and size	
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y	810.0
z	0.0
Rotation	0.0
Advanced	
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Text: text15

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General	

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Lock	false
Text	
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Appearance	
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z	0.0
Rotation	0.0
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Text: text16

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Text	
Text	NumTrucks
Appearance	
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Position and size	
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y	1130.0
z	0.0
Rotation	0.0
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Text: text17

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Show at runtime	true
Lock	false
Text	
Text	Completed%
Appearance	
Color	darkBlue
Alignment	LEFT

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Position and size	
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Rotation	0.0
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Text: text18

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General	
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Lock	false
Text	
Text	NumTrucks
Appearance	
Color	darkBlue
Alignment	RIGHT
Position and size	
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y	1520.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Text: text19

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General	
Show at runtime	true
Lock	false
Text	
Text	NumTrucks:
Appearance	
Color	darkBlue
Alignment	RIGHT
Position and size	
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y	1100.0
z	0.0
Rotation	0.0
Advanced	
Show name	false

Button: button

null	null
General	
Dynamic: Enable	getState() == IDLE
Enabled	true
Label text	Run
Action	
Action	run();
Position and size	
x	40.0
Width	100.0
y	80.0
Height	30.0
Advanced	
Show name	false

Database: Database

null	null
Log	
Logging	true

VITA

Jooho Kim was born in Seoul, South Korea and received his Bachelor of Science in Architectural Engineering at University of Seoul. After his graduation, he worked at BaMI (Builders as a Mission International), non-profit organization, for two years. He started his Master program in the School of Civil Engineering at Purdue University. The title of his master thesis was

He continued PhD program under the guidance of Dr. Makarand Hastak. The title of his dissertation was adaptive system of systems approach to navigate complexity of post-disaster debris management.

PUBLICATIONS

International Journal of Disaster Risk Reduction xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

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

A framework for assessing the resilience of a disaster debris management system

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ARTICLE INFO

Keywords:
Disaster debris management
GIS
Critical infrastructure
Capacity building
Resilience

ABSTRACT

Disaster debris management plays a critical role in expediting the disaster recovery process. This study aims to present a framework for effective disaster debris management for a resilient community. The framework consists of a Geographical Information System (GIS) and system dynamics to assess debris removal performance.

GIS was used to conduct a land suitability analysis for a temporary debris management site and system dynamics were applied to evaluate the debris removal performance in different scenarios.

This systemic approach and quantitative analysis enable a decision maker to gain insights into the inter-relationship between critical infrastructure and resources, the effectiveness of temporary debris management sites, and the debris removal performance. Also, a debris management team would have benefits from the framework by being able to (1) understand dynamic behaviors of debris removal operation, (2) evaluate the existing debris management plan, and (3) set up multiple strategies for optimal debris removal operations under different disaster-impact scenarios.

1. Introduction

Recent research shows that the world is experiencing more extreme natural hazards such as hurricanes, floods, earthquakes, and tsunamis [1]. The experiences with recent disaster recovery efforts have highlighted the need for additional guidance, structure, and support to improve the response to disaster recovery challenges.

Disasters generate an exceptionally large amount of debris, causing considerable processing and disposal challenges [2]. In the past, a primary objective was to transport the debris generated by disasters from an original site to its final destination as soon as possible. Consequently, the debris generated was simply buried or burned [3]. Historically, the volume of debris has been about five to ten times the annual solid waste generation in a community [4,5]. This huge amount of debris causes delays in the debris removal operation and other emergency responses. It results in the delay of the entire disaster recovery process.

For example, the 13 million cubic yards (CY) of debris generated in the 2010 Haiti earthquake hampered emergency response and recovery projects [6]. Debris cleanup was also delayed by damaged infrastructure and insufficient resources. After several months, the destruction continued to disrupt the lives of many Haitians. Cholera outbreaks began in October 2010 and killed at least 7000 Haitians. It was recorded as the worst epidemic among the epidemics in recent history [7]. While the Haitian government identified debris removal as one of the top priorities, only 3–10% of the total debris generated had been removed after 12 months [8]. Lack of infrastructure and insufficient resources also hampered the disaster recovery in Haiti.

A framework for effective debris management is crucial to building community resilience.

There is a need for a framework to assess debris removal system and performance under the interrelationship of critical infrastructure and resources. Therefore, this study presents a framework for developing an effective disaster debris management for local governments and emergency agencies. The specific objectives are to:

- Establish the interrelationship between critical infrastructure (CIs) and the waste management system.
- Develop a temporary debris management site selection model.
- Develop a system dynamic model to understand the complex behavior of the debris removal system and identify unexpected bottlenecks from a system viewpoint (i.e., TDMS impacts, shortages of required resources, and infrastructure capacity during debris removal operations).
- Support disaster debris managers with multiple debris removal operational strategies.

The remainder of this study is organized as follows. Section 2 discusses disaster debris management and the results of the literature review. Section 3 describes the suggested framework and methodology applied in this

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https://doi.org/10.1016/j.ijdrr.2018.01.028
Received 14 December 2017; Received in revised form 24 January 2018; Accepted 24 January 2018
2212-4209/

Please cite this article as: Kim, J., International Journal of Disaster Risk Reduction (2018), https://doi.org/10.1016/j.ijdrr.2018.01.028

study. Section 4 discusses results from tested scenarios. Finally, Sections 5 and 6 conclude the study and present future research directions.

2. Literature review

2.1. Debris removal

A debris removal operation has two phases: response and recovery [9]. In the response phase, the main objective is cleaning up the debris on emergency access routes immediately after a disaster. In the recovery phase, debris on the public right-of-way is removed. According to the national disaster recovery framework by FEMA, debris removal activities are in phases 2 and 3 [2].

– Phase 1: Pre-Disaster Preparedness.
– Phase 2: Post-Disaster Short Term (days to weeks)
  o Debris: clear primary transportation routes.

– Phase 3: Post-Disaster Intermediate Term (weeks to months)
  o Debris: Initiate debris removal on curbside.

– Phase 4: Post-Disaster Long Term (months to years).

It was identified that much of the literature categorized debris removal in the recovery phase and there were a few studies considering the debris removal as a prerequisite for emergency responses such as emergency rescue, medical care and evacuation [10]. They investigated debris removal operations in the emergency phase and suggested a resource routing model to clean up debris on roadsides in order to increase access of emergency relief suppliers to disaster-affected regions.

Several studies investigated debris removal in the recovery phase, e.g., resource (vehicle) routing and management to improve debris removal performance. Brooks et al. [11–13] presented a model for dynamic allocation of debris removal trucks in closed queueing networks using queueing theory to improve debris removal performance. Brooks and Mendonca [12] studied the optimal hauling trucks mix from two perspectives (efficiency and equity). A spreadsheet-based decision support tool was developed and illustrated the applicability and effectiveness of the tool with a disaster scenario based on Hurricane Andrew [14–16]. While the literature suggested multiple methods to optimize either a component of the debris management system or the entire debris management system, it is limited in its understanding of the dynamic behaviors of a debris management system under the interrelationship with CIs. System dynamics is a well-established method for studying and managing complex systems and many solid waste management systems have been examined by this method [17–22].

2.2. Temporary debris management site

A temporary debris management site (TDMS) is sometimes called a temporary staging site, temporary debris management area, temporary debris storage and processing facility, temporary debris storage and reduction site, or a temporary disaster waste management site [23–27]. A TDMS is a designed buffer to sort, recycle, and dispose of the debris generated. To process one million cubic yards of debris (754,555 m^3) 100 acres of land (0.4 km^2) is required [9]. Several agencies have emphasized the importance of TDMS for effective debris management [28–30]. However, unsuitable TDMS locations in areas near playgrounds, swamps, and rice paddies have been cited as potentially damaging to the environment and affecting the livelihood of people in a community [31,32]. It also can attract vermin such as rodents and other pests, produce noise and odors at levels deemed unacceptable by residents, or place a large burden on normal traffic patterns [9,33]. To prevent these negative effects, US EPA (U.S. Environmental Protection Agency)and UNEP (United Nation Environment Programme) provided the following suggestions for a TDMS [29,30]:

- Sufficient in size with appropriate topography and soil type.
- Appropriate distances from potable water wells, rivers, lakes, and streams.
- Not in a floodplain or wetland.
- Controls in the TDMS to mitigate stormwater runoff, erosion, fires, and dust.
- Free from power lines and pipelines.
- Limited access to only specific areas open to the public such as areas to drop off debris.
- Located close to the impacted area but far enough away from residences, infrastructure, and businesses that could be affected by site operations.
- Preferably located on public land because approval for this use is easier to obtain, but it could also be located on private lands.

Identifying potential TDMS locations is considered as land use suitability assessment. Kim et al. [34] conducted spatial analysis to determine a TDMS location within certain environmental constraints. Grzeda et al. [26] identified potential TDMSs by using binomial cluster analysis and GIS. Cheng and Thompson [27] reviewed 50 recently published articles and summarized the criteria of land suitability assessment in three areas (using environmental, social-cultural, and economic-engineering criteria). They used Boolean logic and GIS to determine suitable locations for TDMSs. These studies are limited to considering environmental regulations to install a TDMS excluding the technical perspective to expedite debris removal performance. Many studies in the literature have referred to the fact that either double handling of debris generated or acquiring lands for TDMSs could result in higher debris removal operation costs [9,23,35,36]. Thus, it is critical to evaluate the impacts of TDMS location and capacity on debris removal performance.

2.3. Critical infrastructure

Tierney and Bruneau [37] emphasized that critical infrastructures, including transportation and utility lifeline systems, are essential to enhance resilience in a community in terms of four determinants: *robustness, redundancy, resourcefulness,* and *rapidity*. Guerrero et al. [38] studied various factors which impact the solid waste management system for each activity (see Table 1). They identified the essential infrastructure needed, such as transportation systems, technologies, and facilities for treatment, recycling, and disposal. Required resources were identified as hauling vehicles, incinerators, and chipping and grinding equipment [35] as well as proper knowledge of treatment, disposal, and recycling of waste [38].

Deshmukh and Hastak [46,47] suggested a framework for expediting community post-disaster recovery through capacity building resulting from

Table 1
Factors influencing waste management systems.

Activity	Factors
Collection, Transfer, and Transport	Poor route/improper bin collection [39] Infrastructure/vehicle for waste collection [40] Organization of the informal sector [41] Quality of roads [42] Transportation facility available [42]
Treatment	Knowledge of treatment systems by authorities [43] Suitable infrastructure [42] Local knowledge of waste management issues [42]
Disposal	Supply of containers and distances [44] Priced disposal [44]
Recycling	Organization of informal sector [41] Collection of recyclables supported by companies [45] Efficiency collection system [42]

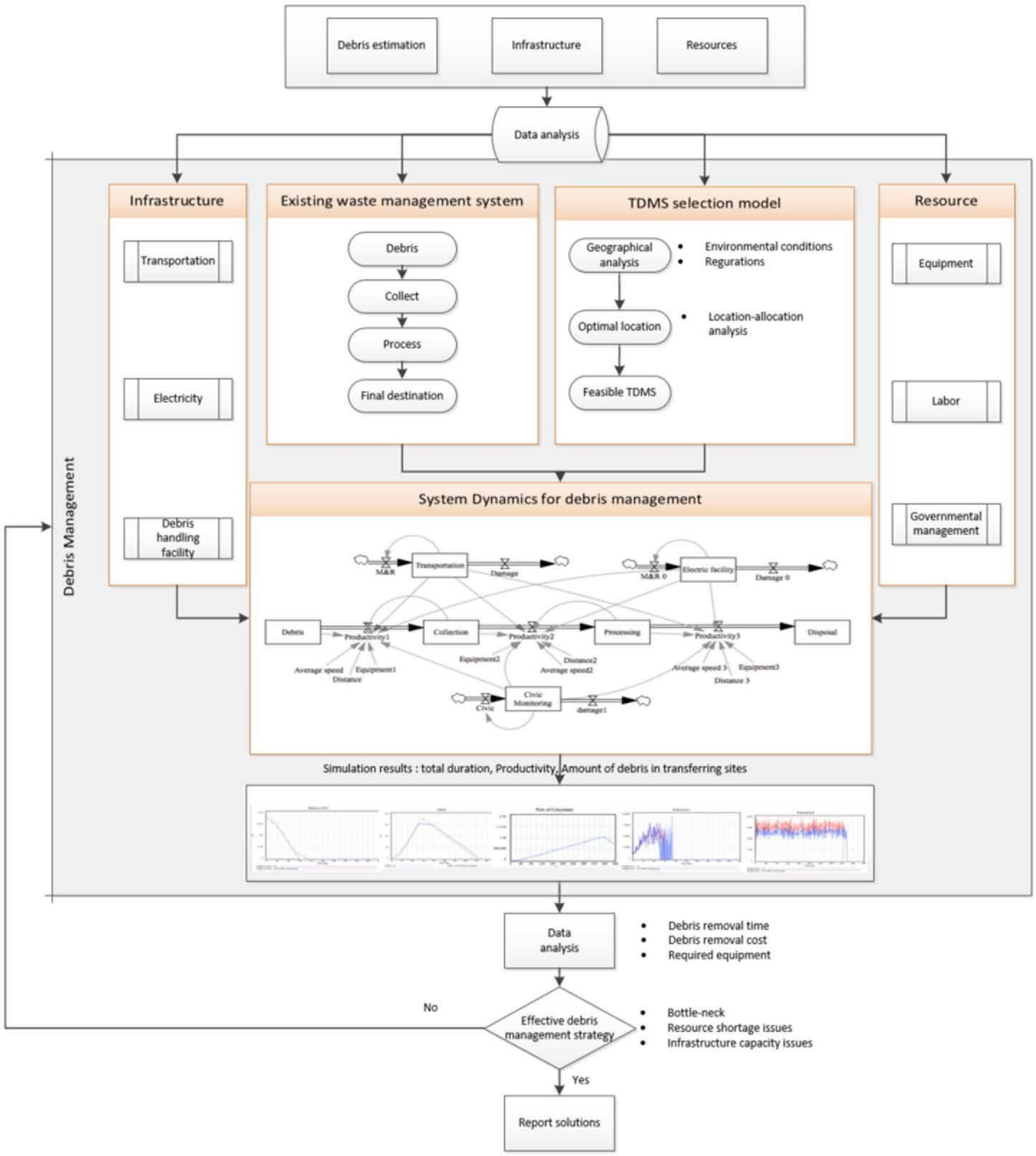

Fig. 1. Framework for a debris management system.

enhanced infrastructure performance. The framework integrated the results available from loss assessment tools and locally available data while exploring the interrelationship between communities, industries, and related critical infrastructure. Oh et al. [48,49] concluded that the impact of disasters is further escalated by the failure of critical infrastructure in a community and that such failures are significantly related to the conditions of critical infrastructure. To enhance resilience in the face of a disaster, the debris management team should identify both the current solid waste management system and required debris management system to build a sufficient capacity to handle the debris generated [50].

There are several studies aimed at coordinating debris removal from road networks to increase performance of the road network after a disaster. Chang and Nojima [51] developed post-disaster transportation performance measures using network coverage and transport accessibility. Özdamar et al. [52] applied the measure of network accessibility and proposed a mathematical model that maximizes cumulative network accessibility by

Table 2
Test scenarios.

The number of TDMS	The number of trucks		
1	180 ([a]T1R180)	210 (T1R210)	240 (T1R240)
2	180 (T2R180)	210 (T2R210)	240 (T2R240)
3	180 (T3R180)	210 (T3R210)	240 (T3R240)

[a] T#R# indicates a case number. e.g., T1R180 represents 1 TDMS and 180 trucks being operated in the scenario.

Table 3
List of attributes.

List	Attributes	Description
Population	2,500,000	
Community size	6060 km^2 (= 2430 $mile^2$)	1 $mile^2$ = 2.59 km^2
Disaster type	Hurricane	Category 4, 10 year event
Debris generated	419,234 t (1,676,936 CY[a])	1 t = 4CY[a] [63] Mixed debris (concrete, steel and vegetative)
Recycling facility	1	Recycling rate RANDOM NORMAL (0.05, 0.015, 0.08) Min Max Mean
Landfill	1	
Civic monitoring	Good Schaufelberger (1999)	
Job condition	Fair to Good Schaufelberger (1999)	
Initial numbers of trucks	Collection points to TDMS = 30 EA TDMS to Recycling facility = 60 EA TDMS to Landfill = 90 EA	
Truck capacity	13.7 m^3 (18 CY[a])	[64]
Truck speed	In a community: 40 km/h (25 mph) In highway: 72 km/h (45 mph)	
Transportation damage	65%	Repair rate RANDOM NORMAL (0.007, 0.015, 0.012) Min Max Mean
Electric facility damage	50%	Repair rate RANDOM NORMAL (0.009, 0.012, 0.010) Min Max Mean

[a] CY = cubic yard.

the debris removal operation and minimizes the total length of travel time (makespan). Ertugay et al. [53] studied road accessibility modeling in an earthquake by road closer probabilities. Zanini et al. [54] explored road network functionality in relation to building damage. These can be applied to select TDMS locations as well as prioritize debris cleanup on the roadside to increase the performance of the entire debris removal operation.

3. Methodology

A framework is crucial for debris management teams to evaluate and enhance their debris management systems. The proposed framework will help in preparing a debris management plan as well as enhance system performance for post-disaster debris management. It would enable emergency agencies to identify TDMS locations and evaluate the complex debris removal system behaviors under the different debris removal scenarios (see Fig. 1).

3.1. GIS data collection and debris estimation

GIS data are required to effectively develop a disaster debris management plan and to operate debris removal in a post-disaster phase. Required data are (1) details of the existing waste management system (recycling facilities, transfer stations, and landfills), (2) serviceability of the infrastructure (transportation and electric power facility) and equipment (hauling trucks, loaders, grinders, and incinerators). For this study, GIS data were collected from Florida Department of Transportation (FDOT) and the GeoPlan Center at the University of Florida [55,56].

To estimate the debris generated by a disaster, this study used Hazus-MH, the risk assessment tool developed by FEMA [57]. It uses demographic and geographic data with structural analysis methods to estimate physical damage including the debris composition and amounts (www.fema.gov/hazus). Ding and Spinks [58] validated the debris estimation tool for Hurricane Ike and determined a resulting error of only 4.6%. This tool has been used in numerous studies related to disaster management [14,15,50,53,59–61].

3.2. Module 1 TDMS selection model

This is designed to identify optimal TDMS locations and may be used to minimize unexpected environmental issues around TDMSs. The TDMS selection model consists of two sub-modules; (1) A geographical analysis is to identify feasible areas for TDMSs and (2) location-allocation analysis searches for optimal TDMS locations in the feasible areas.

3.3. Module 2 system dynamics

A system dynamic model is constructed to understand and examine dynamic behaviors of a complex debris management system in different scenarios. Simulation results will be used to evaluate the debris management system and estimate the total cost and time for debris removal. This study used Vensim (version 6.4) to develop the system dynamic model [62].

4. Test scenarios

This study performs tests of the proposed framework in a post-hurricane scenario. The community population considered is 2.5 million and the corresponding area is 2430 $mile^2$ in a very high-risk of hurricane damage zone (Florida, USA). As of 2017, there were 79 tropical or subtropical cyclones in the community. The Hazus-MH creates a hurricane event (hurricane category 4, 10-year event) and generates 1676,936 Cubic Yards (CY) of mixed debris in the community.

There are nine scenarios in terms of the number of hauling trucks and TDMSs (see Table 2). The case number describes the number of TDMSs and trucks operated for each. For example, T1R180 represents the operation of one TDMS and 180 hauling trucks.

In the scenarios, we assume the following.

- Mixed debris in a community are hauled to designated TDMSs and then segregated.
- Truck speed is 25 mph (40 km/h) on local and 45 mph (72 km/h) on highway
  o There are sufficient loaders and manpower.
- There is no weather constraint during debris removal operations.
- The list of attributes is given in Table 3.

4.1. TDMS selection model

4.1.1. Geographical analysis

As mentioned in Section 2.2, a TDMS plays an important role in post-disaster debris management to increase the performance of debris removal operations. Most state-level agencies in the United States have provided guidelines to site a TDMS to minimize environmental impacts and help identify potential TDMS locations [65–67].

However, the existing guidelines and potential TDMS location would not be able to maximize debris removal performance by disaster type and

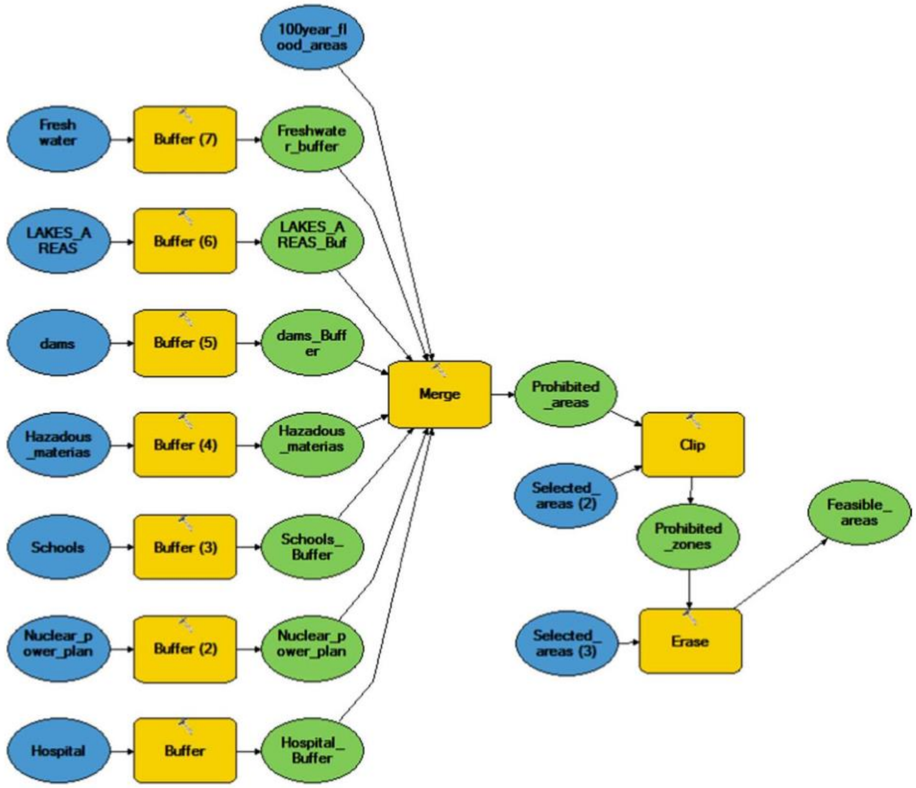

Fig. 2. ModelBuilder in the TDMS selection model.

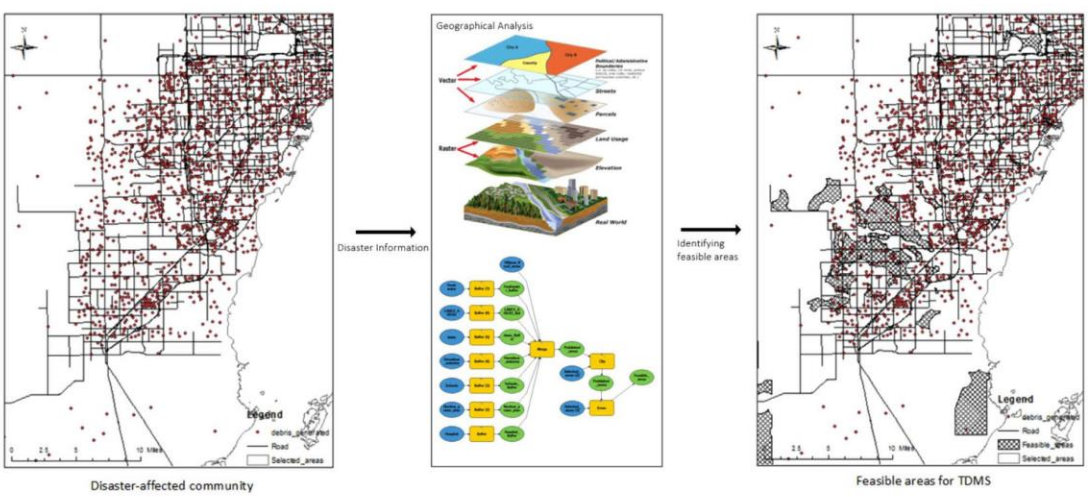

Fig. 3. Process of geographical analysis * Debris location = •.

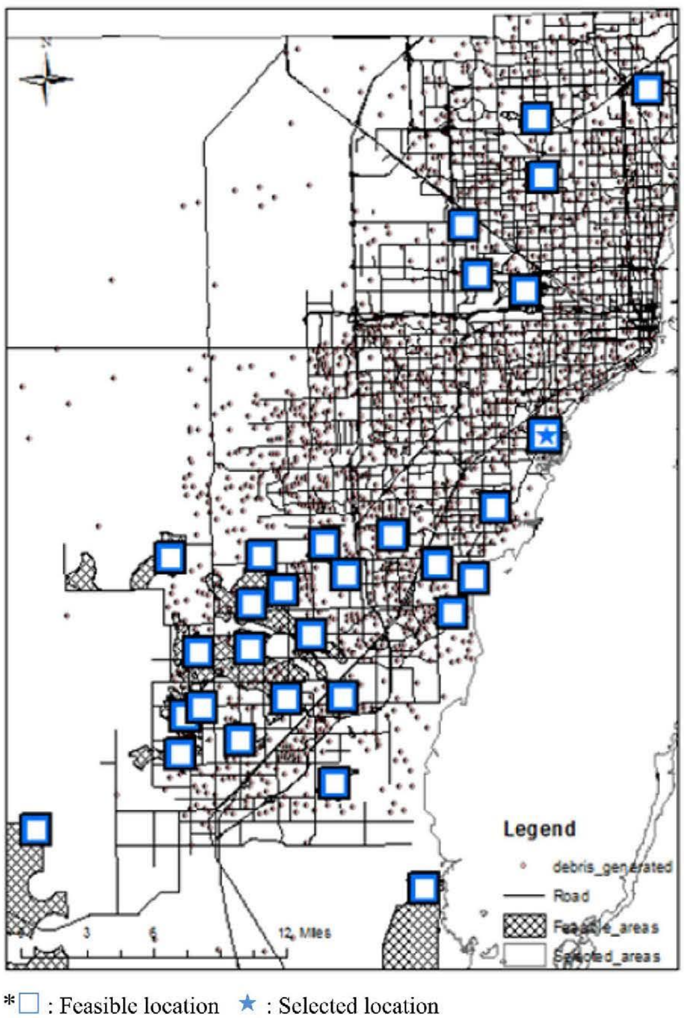

Fig. 4. Selected TDMS location (T1R#).

impact, community needs, and other emergency planning factors such as shelter location and emergency medical service location. A decision process for a TDMS location involves numerous variables, constraints, and jurisdictions during pre- and post-disaster management. This study considers the following criteria (site regulations) to identify feasible TDMS locations based on the guidelines by US EPA and FEMA.

– Water sources (groundwater, fresh water, dams, and lakes).
– Public facilities (hospitals, schools).
– Hazardous material management facilities.
– 100-year floodplain.

To identify feasible locations for TDMSs, ModelBuilder in ArcGIS is used. It is a visual programming language for building geoprocessing workflows. It also automates and documents spatial analysis and data management processes [68]. The model created for identifying TDMS locations is described in Fig. 2. Buffer polygons (500 m, 0.31 miles) around input features are created and then merged to create prohibited areas. Then, the clip and erase tools are used to identify feasible areas.

The overall process of geographical analysis and the result are described in Fig. 3. Collected GIS data and information are geo-processed by the ModelBuilder. Feasible areas for TDMS are represented by gridded polygons.

4.1.2. Location-allocation analysis

Most of the debris removal operation costs are incurred from transporting debris [69]. The hauling performance depends on the number of trucks, truck capacity, and the cycle time. The cycle time is determined by defining haul boundary, dump locations and loading locations [70]. Since the location of a TDMS directly affects truck cycle time, it should be located in an area designed to minimize the truck cycling time. TDMSs location is considered with the P-Median problem [71]. Location-allocation analysis for the P-Median problem is applied to identify a TDMS location that minimizes the total hauling distance

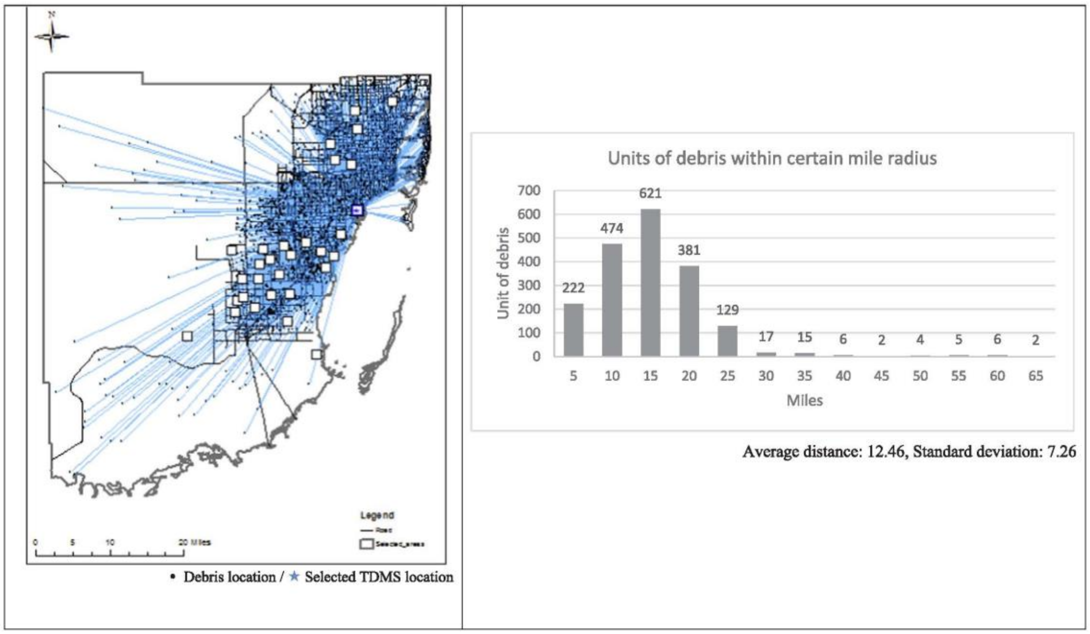

Fig. 5. TDMS selection model result (T1R#).

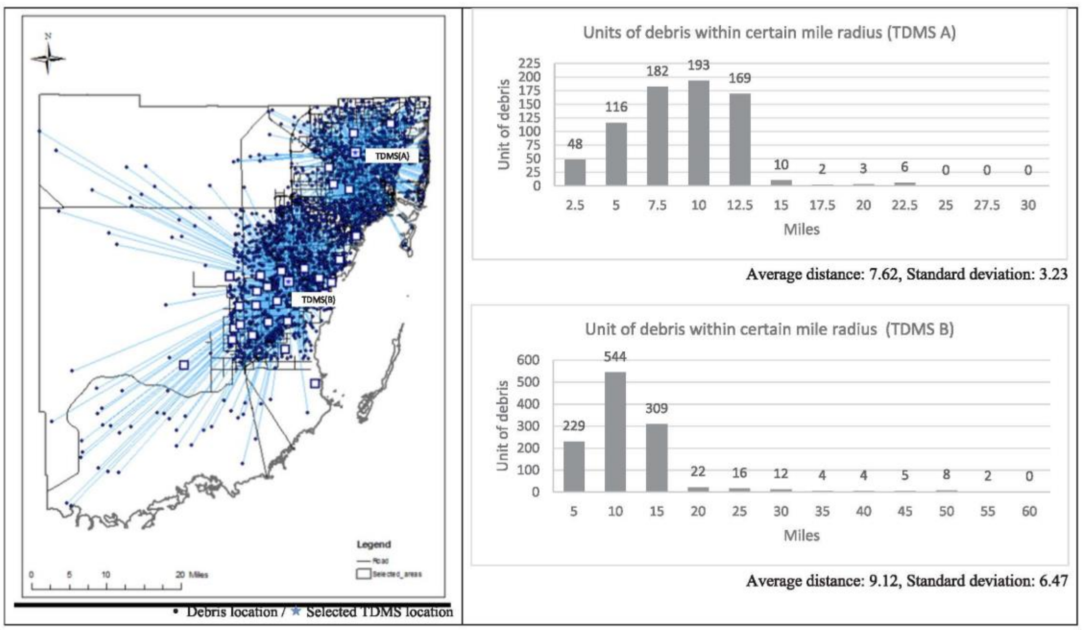

Fig. 6. TDMS selection model result (T2R#).

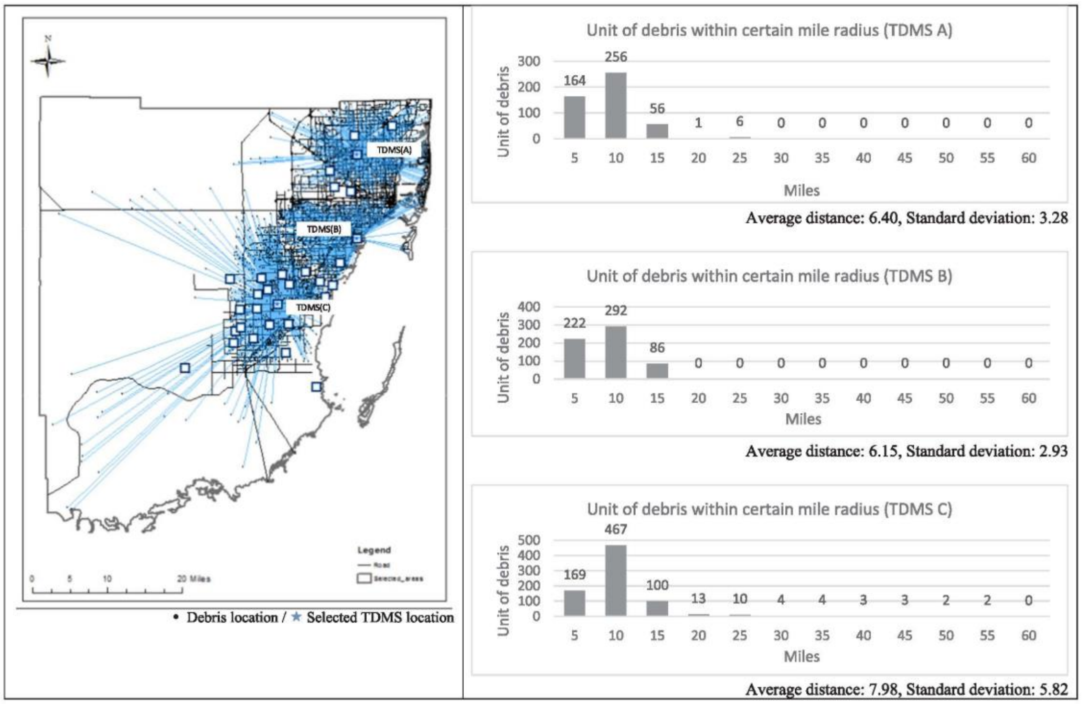

Fig. 7. TDMS selection model result (T3R#).

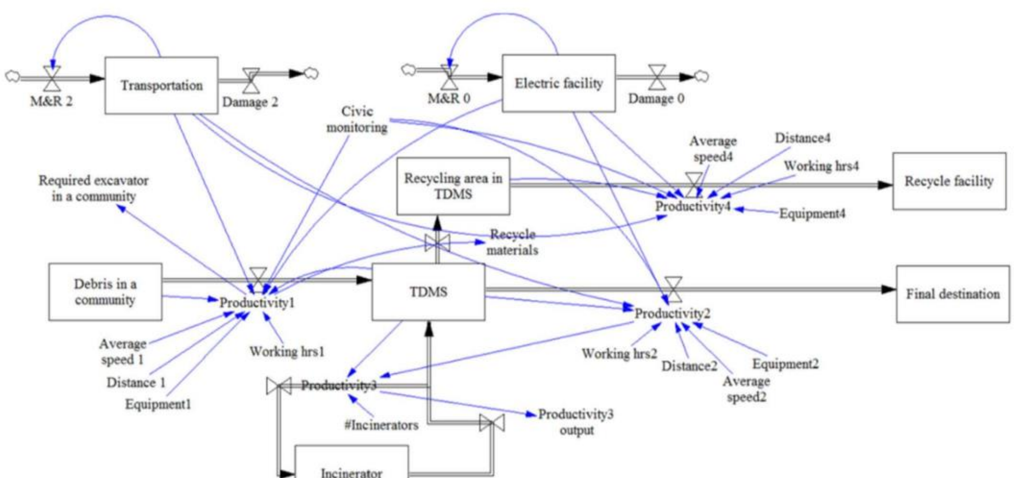

Fig. 8. Model Structure *Equations in box variables and rate arrows are described in Tables A.1 and A.2.

from the collection points (debris locations) to the TDMS among the TDMS candidates.

Input

h_i = *Debris i demand*

d_{ij} = *distance between debris i and candidate facility j*

P = *number of facilities to locate*

Decision variables

Table 4
Efficiency factor [75].

Job Condition	Management condition			
	Excellent	Good	Poor	Fair
Excellent	0.84	0.81	0.76	0.70
Good	0.78	0.75	0.71	0.65
Poor	0.72	0.69	0.65	0.60
Fair	0.63	0.61	0.57	0.52

$$x_i = \begin{cases} 1 & \textit{if we locate at candiate site } j \\ 0 & \textit{if not} \end{cases}$$

$$y_{ij} = \begin{cases} 1 & \textit{if customer } i \textit{ is served by facility } j \\ 0 & \textit{if not} \end{cases}$$

Minimize

$$\sum_i \sum_j h_i d_{ij} Y_{ij} \qquad (a)$$

Subject to

$\sum_j Y_{ij} = 1 \quad \forall\ i \quad (b)$ *required that each debris is assigned to exactly one facility*

$\sum_j X_j = P \qquad (c)$ *requires that exactly P facilities are located*

$Y_{ij} - X_j \le P \quad \forall\ ij$ *(d)link the location variables and the allocation variables*

$Y_{ij} = 0, \quad 1 \quad \forall j$ *(e)allocation variables (Y) are binary*

$X_j = 0, \quad 1 \quad \forall ij$ *(f)location variables (X) are binary*

This study applied the vertex substitution heuristic algorithm to find a TDMS location [72,73]. An example of the result is described in Fig. 4.

4.1.3. Results

Figs. 5–7 describe selected TDMSs among the TDMS candidates. A map on the left describes the location of the TDMS represented with a blue star in a box. The blue lines refer to the debris assigned to a connected TDMS. Descriptive statistics for the distance between debris location and selected TDMSs are described on the right. By increasing the number of TDMSs, the average distance and standard deviation are significantly decreased.

4.2. System dynamic model

As discussed in Section 2, debris removal performance depends on the existing solid waste management system, available resources, and serviceability of critical infrastructure including transportation, electric power facilities and civic monitoring systems. As discussed in Section 4.1.3., the number and location of TDMSs is one of many critical factors determining the overall debris removal performance. To analyze the complex system and the dynamic behavior of debris management system during disaster responses, this study developed a system dynamic model. The basic system dynamic model structure is described in Fig. 8.

The system dynamics consists of *box variables* and *rate arrows below.*

- Box variables (unit: CY/day)
  - o Debris in a community
  - o TDMS
  - o Incinerator (type: air curtain incinerator installed in the TDMSs)
    - ■ Average throughput: 6–10 t/h [74]
  - o Recycling facility
  - o Final destination (Landfill)
- Rate arrows: Productivity 1,2, 3, and 4 (unit: CY/day)
  - o Productivity 1: debris hauled to the TDMS.
  - o Productivity 2: debris taken from TDMS to the final destination.
  - o Productivity 3: debris incinerated in the TDMS.
  - o Productivity 4: debris taken from TDMS to the recycling facility.
  - o M&R: infrastructure maintenance and repair.
  - o Damage: damage to the serviceability of the infrastructure by a disaster.
- *Serviceability of infrastructure (transportation, electric power facilities, civic monitoring system).*

Schaufelberger [75] studied equipment productivity estimation (see Eq. (1))

$$\textbf{Productivity} = \frac{\textbf{Efficiency} \times \textbf{Capacity}}{\textbf{Cycle time}} \qquad (1)$$

Capacity is determined by the type of hauling methods. Cycle time is the sum of the loading, hauling, dumping, and returning times of the hauling methods. Efficiency is determined by job and management condition [75] (see Table 4).

To determine the *efficiency* of debris removal operation, this study assumes the following:

- Job condition is determined by the serviceability of transportation and electric power facilities [38,40].
  - o *Fair* is selected when the serviceability of transportation and electric facilities reach 40%.
  - o *Excellent* is selected when the serviceability of transportation and electric power facilities reach 100% (fully functioning system).
  - o *Serviceability of transportation more significantly affects the debris removal operation than the electric power facilities* [76]
    - ■ Serviceability of transportation is given a weight of 2.
    - ■ Serviceability of electric power facilities is given a weight of 1.
- Management condition is determined by a civic monitoring system [77].
  - o Civic monitoring system is *"good."*

With the assumptions above, Eq. (2) is used to determine efficiency over time in the system dynamics.

$$Efficiency = \frac{0.35(2 \times ST + SE)}{3} + 0.47 \qquad (2)$$

ST : *Serviceability of transportation* SE : *Serviceability of electric power facility*

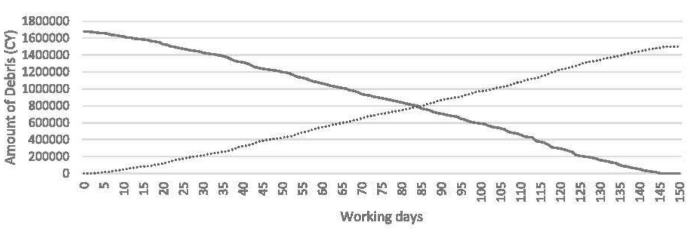

Fig. 9. Amount of debris in the community and final destination over time.

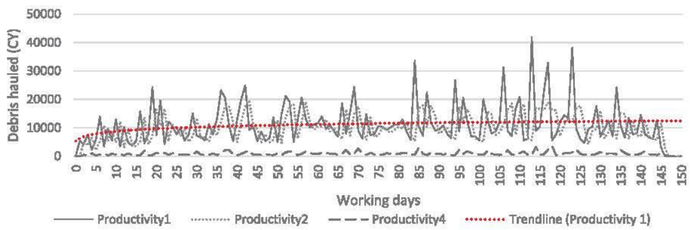

Fig. 10. Daily productivity (amount of debris hauled to a next station).

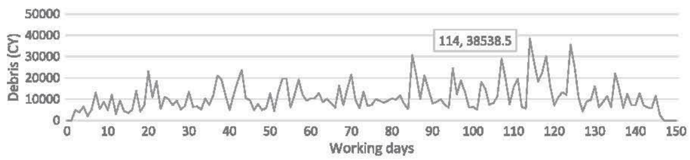

Fig. 11. Amount of debris in the TDMS over time.

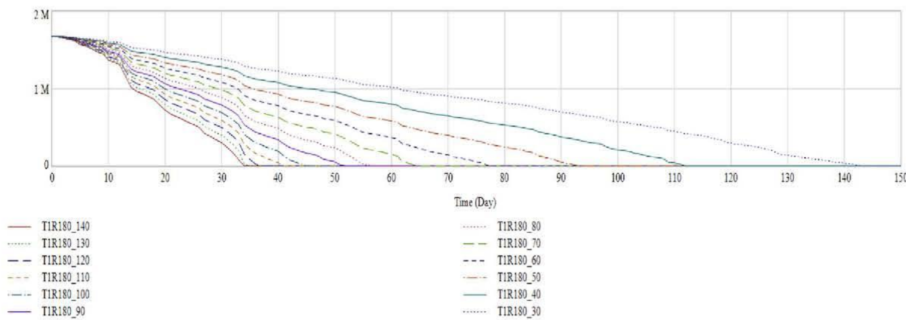

Fig. 12. Debris in a community *T1R180_#: # indicates the number of equipment#1.

4.3. Results

The simulation result of scenario T1R180 is described in Fig. 9. The total working days for debris removal from the community is 145 days; it takes two more days to haul debris from the TDMS to the final destinations. The estimated cost is determined as $54,937,106 to clean up the 1.67 M CY debris generated (the detail of the operation cost is described in Table A.3).

The daily productivity is described in Fig. 10. Productivity 1 (from collection points to TDMS) fluctuates widely compared to Productivities 2 and 4 because the dispersed debris locations affect the travel distances of trucks; the average distance from the debris locations to the TDMS sites is 12.5 miles and the standard deviation is 7.26 miles (see Fig. 5). The overall performance of Productivity 1 is increasing because the serviceability of the infrastructure (transportation and electric facilities) is recovered over time.

The fluctuating debris throughput (Productivity 1) significantly affects the daily amount of debris in the TDMS (see Fig. 11). However, the amount of debris does not exceed the designed capacity, 1 M CY, during working days. The maximum amount of debris is 38,538.5 CY at day 114.

For sensitivity analysis, OFAT (one-factor-at-a-time-method) is conducted. An input variable, Equipment#1, is increased from 30 to 140. The increased number of Equipment#1 reduces the debris removal time in a community (see Fig. 12). The rate of change of Equipment #1 is decreasing since the capacity in other system areas could not support further increase to the system input. Also, the number of Equipment#1 could not be over 140 because this reaches the maximum TDMS capacity, 1 M CY at day 35.

The overall system behaviors are described in Fig. 13. Productivities 2, 3, and the recycled materials output systems are significantly stabilized by increasing the number of Equipment#1. In the case that the number of Equipmen#1 is lower than 60, some components of the system need to be idle or be operated at under 60% of the capacity (Productivities 2, 3, and recycled materials) until further debris enters the system.

5. Conclusions

This study tested nine scenarios to understand the dynamic behaviors of debris removal performance. The operation cost and time are described in Fig. 14. The range of total costs is from $34,999,241 (T3R240) to $56,525,977 (T1R180). The range of total working days for debris removal is from 70 (T2R240) to 147 (T1R180) days. While the total working days are decreased by increasing the number of TDMSs and resources, the effectiveness in debris removal performance was examined by system dynamics to maximize operational efficiency and to identify any bottlenecks in the text scenarios. According to FEMA's pilot program related to debris management, reimbursement provided to sub-recipients is based on the federal cost share percentages; when debris removal finishes within 90 days, 80% of the cost will be reimbursed by the federal government [78]. Most state-level agencies in the United States have designed their debris removal plans to finish debris removal operations within 90 days.

In this study, the case T3R240 is selected as an optimal solution for debris removal ($34,999,241, 70 days) among the nine test scenarios. Comparison of T1R180 and T1R210 demonstrates that increasing the number of resources reduces the total cost as well as the working days. The debris collection time from collection point to a TDMS is decreased by 46% (147 to 80 days). The debris hauling time from a TDMS to a final destination is decreased by 39% (144 to 88 days).

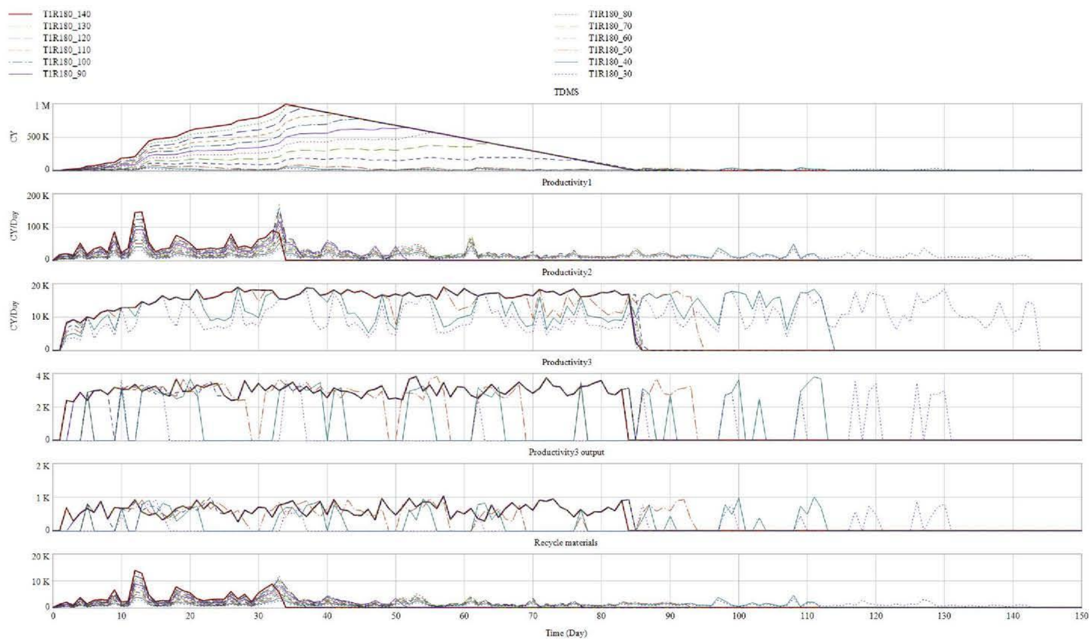

Fig. 13. System behaviors – causes strip of TDMS (T1R180).

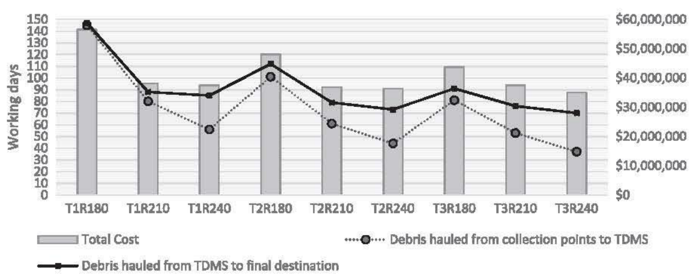

Fig. 14. Operation cost and time by scenario.

While increasing resources from 210 to 240 (T1R210 to T1R240) slightly affects the total working days and cost, debris collection time from the collection points was decreased by 30% (80 to 56 days).

The results also demonstrate that balancing between infrastructure capacity and resources is critical to optimize the debris removal operation. For example, comparison of T2R240 and T3R210 identifies that additional TDMSs did not have a positive effect of the total cost: (1) total working days is 73 in T2R240 and 76 in T3R210 and (2) the total cost of T2R240 ($36,337,017) is less than T3R210 ($37,464,923). Comparing to T2R240, T3R180 has another TDMS. However, it results in extra expenses to acquire the land and the shortage of resources hampered the debris removal process.

6. Discussions

This study suggested a framework for effective debris management for a resilient community. It provided a guideline to support debris management teams in developing effective debris removal strategies. The systemic approach and quantitative analysis enable decision makers to gain insights into the inter-relationship between critical infrastructure and resources, the effectiveness of operating TDMSs, and debris removal performance according to different strategies. The nine test scenarios evaluated the effectiveness of the debris removal strategies in terms of the number of TDMS and resources.

The proposed framework will allow decision makers to comprehend the required budgets and time for debris removal in a timely manner. For example, local municipalities/agencies would be able to incorporate their past disaster debris removal data into the proposed framework to compare the differences between actual and estimated cost obtained from the system.

Also, the proposed framework can evaluate an existing debris management system to enhance its resiliency under different disaster scenarios. A debris management team would be able to simulate the existing debris management system using the proposed framework to identify any bottlenecks or points of insufficient capacity of facilities. As discussed in Section 4.3., the input variables, such as the number of trucks at each stage or the capacity of the debris-handling facilities, significantly affect the system efficiency. In the given condition, more than 140 trucks could not be utilized because this would exceed the designed TDMS capacity, 1 M CY. Thus, other strategies would be vital to process increased debris throughput in the TDMSs: (1) increasing initial TDMS capacity by selecting other locations in a design phase, (2) increasing the number of trucks hauling the debris to recycling facilities or landfills in an operational phase, or (3) operating additional equipment to reduce the volume of debris in the TDMSs such as incinerators and chippers. These options would be evaluated by the proposed framework to increase the robustness of debris removal operations.

This study can be expanded in several ways. Real-time or dynamic resource allocation needs to be explored to stabilize debris throughput in the TDMSs. Further, the design of a TDMS needs to be considered to handle debris effectively in terms of capacity, routing system, and equipment operations (loaders, incinerators, and chippers). In addition, different types of disasters affect the serviceability of infrastructure in different ways; sometimes, it can entirely lose its function during disaster recovery. These infrastructure interdependencies of debris management would be a topic of future research.

The frequency of natural disasters is increasing every year around the world. Numerous emergency agencies have recognized the crucial role of disaster-related data and information to mitigate the impacts of disasters. Thus, local government and emergency agencies need to develop a database for the past disaster debris management strategies and operations. It will allow emergency agencies, policymakers and researchers to develop better disaster planning for preparedness, responses and recovery.

Appendix A

(See Tables A1–A3).

Table A.1
Equations in the box variables and rates.

Type	Equations
Debris	= IF THEN ELSE(Debris > 0,-Productivity1,0)
Collection	= - Productivity2 + Productivity1
Processing	= +Productivity2-Productivity3
Recycling area in TDMS	= Recycle materials 1-Productivity4
Disposal	= INTEG(Productivity3)
Productivity1	=STEP(IF THEN ELSE(Collection < 30000,IF THEN ELSE (Debris > 18*(Equipment1)/(Distance/Average speed/ 2)*Efficiency,18*(Equipment1)/(Distance/Average speed/ 2)*Efficiency,Debris),0),1)
Productivity2	= IF THEN ELSE (Collection > (18*(Equipment2)/ (Distance2/Average speed2/2)*efficiency): OR: Collection > (4500-Processing),min(4500- Processing,18*(Equipment2)/(Distance2/Average speed2/2)* Efficiency),Collection)
Productivity3	= STEP(IF THEN ELSE(Processing > 0,IF THEN ELSE (Processing > Equipment3*18/(Distance 3/Average speed 3/ 2)*Efficiency,Equipment3*18/(Distance 3/Average speed 3/2)* Efficiency,Processing),0),1)
Recycling materials	= RANDOM NORMAL(0.05,0.15,0.08,0.02,9)*Productivity1

Table A.2
Serviceability of infrastructure.

Type	Equation
Transportation	"M&R"-Damage Initial value: 1
Electric	"M&R 0"-Damage 0
Facility	Initial value: 1
Civic	Civic-Damage1
Monitoring	Initial value: 1
M&R	= IF THEN ELSE(Transportation < =1,RANDOM NORMAL (0.007, 0.015, 0.012, 0.008, 2), 0)
Damage	= STEP(.65,0)-STEP(.65,1)
M&R 0	= IF THEN ELSE(Electric facility < =1,RANDOM NORMAL (0.009, 0.012, 0.01, 0.008, 2), 0)
Damage 0	= STEP(.25,0)-STEP(.25,1)
Civic	= 0 (No additional monitoring resources)

Table A.3
Operation cost.

List	Numbers (or size)	Operation cost/unit	References
TDMS	100 Acre	$2000/acre/mo.	[79]
Loaders in TDMS (Cat 950H)	10	$18076/daily (Rent + Fuel + Operator)	[80]
Air incinerator in TDMS	4	$114000(Purchase) + $606.2/day (Fuel + Operator)	[81]
Tub grinder in TDMS	3	$3000(rent) + $6162.6/day (Fuel + Operator)	[82]
Dump truck (CT660)		$1856.68/day (Rent + Fuel + Operator)	[83,84]

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International Journal of Information Management 38 (2018) 86–96

Contents lists available at ScienceDirect

International Journal of Information Management

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

Research Note

Social network analysis: Characteristics of online social networks after a disaster

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ARTICLE INFO

Keywords:
Emergency information
Disaster communication
Social media
Disaster response
Social network analysis (SNA)

ABSTRACT

Social media, such as Twitter and Facebook, plays a critical role in disaster management by propagating emergency information to a disaster-affected community. It ranks as the fourth most popular source for accessing emergency information. Many studies have explored social media data to understand the networks and extract critical information to develop a pre- and post-disaster mitigation plan.

The 2016 flood in Louisiana damaged more than 60,000 homes and was the worst U.S. disaster after Hurricane Sandy in 2012. Parishes in Louisiana actively used their social media to share information with the disaster-affected community – e.g., flood inundation map, locations of emergency shelters, medical services, and debris removal operation. This study applies social network analysis to convert emergency social network data into knowledge. We explore patterns created by the aggregated interactions of online users on Facebook during disaster responses. It provides insights to understand the critical role of social media use for emergency information propagation. The study results show social networks consist of three entities: individuals, emergency agencies, and organizations. The core of a social network consists of numerous individuals. They are actively engaged to share information, communicate with the city of Baton Rouge, and update information. Emergency agencies and organizations are on the periphery of the social network, connecting a community with other communities. The results of this study will help emergency agencies develop their social media operation strategies for a disaster mitigation plan.

1. Introduction

Social media, such as Twitter and Facebook, plays a critical role in disaster management. It is ranked as the fourth most popular source for accessing emergency information (Lindsay, 2011). Mickoleit (2014) identified that government institutions are using platforms such as Twitter, Facebook, and blogs to communicate with their communities. Twitter accounts have been created in 24 out of 34 OECD member countries, which can be compared to 21 out of 34 for Facebook. Many studies have explored the systematic use of social media during emergency responses by extracting social media data to identify needs of a disaster-affected community (Imran, Elbassuoni, Castillo, Diaz, & Meier, 2013; Yin et al., 2015). For example, social media data was used to develop a GIS-based real-time map during 2012 Hurricane Sandy in NYC. It shared emergency information and community needs with emergency agencies and NGOs (Middleton, Middleton, & Modafferi, 2014). Furthermore, real-time data from social media has been used to develop an early warning system for a tornado (Knox et al., 2013; Tyshchuk, Hui, Grabowski, & Wallace, 2011). Social media is used to communicate emergency information and urgent requests between emergency agencies and disaster-affected people (Feldman et al., 2016; Lindsay, 2011). These approaches support emergency agencies in understanding emerging situations rapidly after a disaster.

More than 60,000 homes were damaged in the 2016 flood in Louisiana (Han, 2016). It was the worst disaster after Hurricane Sandy in 2012 (Yan & Flores, 2016). A couple of parishes in Louisiana used their social media to share emergency information with people affected by the disaster. The city of Baton Rouge in Louisiana actively used its social media, such as Facebook and Twitter, to deliver real-time emergency information to the affected people in a timely manner. Few studies have analyzed social network structures and roles during disaster responses. This study applied social network analysis (SNA) to understand the characteristics of social media networks in Louisiana during emergency responses.

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http://dx.doi.org/10.1016/j.ijinfomgt.2017.08.003
Received 30 June 2017; Received in revised form 15 August 2017; Accepted 25 August 2017
Available online 22 September 2017

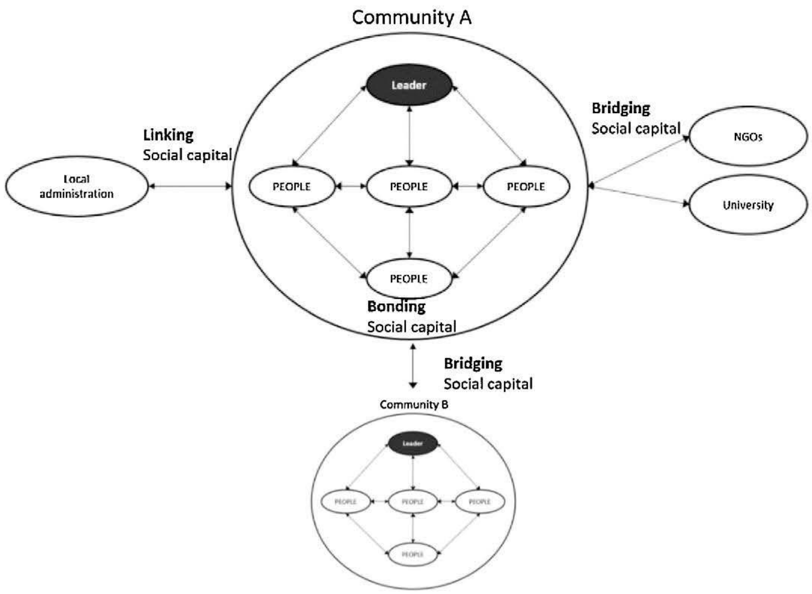


Fig. 1. Conceptual diagram of social capital (Nakagawa & Shaw, 2004).

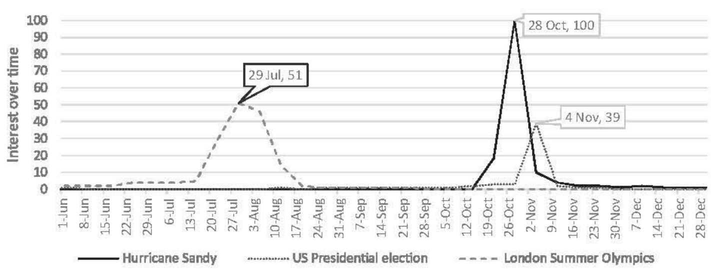


Fig. 2. Search-term comparison during 2012 Hurricane Sandy in the U.S. (Google Trends, 2017a).

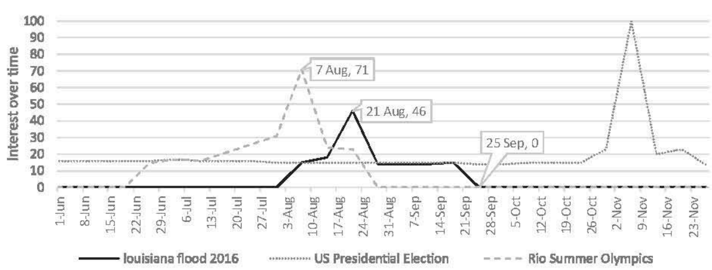


Fig. 3. Search-term comparison during 2016 Louisiana flood in the city of Baton Rouge, Louisiana, USA (Google Trends, 2017b).

2. Literature review

2.1. Social capital for disaster recovery

Social capital can be defined as "the resources accumulated through the relationships among people" (Coleman, 1988). Positive social outcomes from social capital have been identified through public health, lower crime rates, and financial markets (Adler & Kwon, 2002). In general, social capital brings a positive effect of interaction among participants in a social network (Helliwell & Putnam, 2004). Ellison, Steinfield, and Lampe (2007) identified that greater social capital

Table 1
Social media demographics and frequency (Duggan, 2015).

	Facebook	Twitter
18–29	82%	32%
30–49	79%	29%
50–64	64%	13%
65 +	48%	6%
Daily	70%	38%
Weekly	21%	21%
Less often	9%	40%

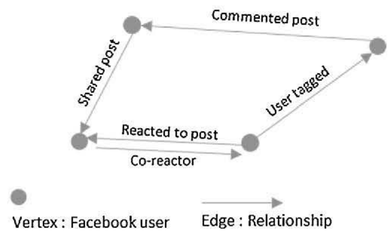


Fig. 4. Illustration of users and relationship.

Table 2
Overall Metrics.

Graph Metric	Value
Graph Type	Directed
Vertices	1171
Unique Edges	21,115
Edges with Duplicates	6400
Total Edges	27,515
Self-Loops	671
Reciprocated Vertex Pair Ratio	0.024
Reciprocated Edge Ratio	0.047
Connected Components	18
Single-Vertex Connected Components	16
Maximum Vertices in a Connected Component	1153
Maximum Edges in a Connected Component	27,510
Maximum Geodesic Distance (Diameter)	5
Average Geodesic Distance	2.41
Graph Density	0.02

increased commitment to a community and the ability to mobilize collective actions.

Many scholars have emphasized that social capital plays a critical role in responses to disasters. Nakagawa and Shaw (2004) examined the post-earthquake rehabilitation and reconstruction programs in two cases: Kobe in Japan and Gujarat in India. They identified that social capital and leadership in the community are the basic attributes for rapid disaster recovery. They described three aspects of social capital: *bonding*, *bridging* and *linking (see* Fig. 1). By investigating disaster recovery after the 1995 Kobe earthquake in Japan, Aldrich (2011) emphasized that the power of people (social capital) is the strongest and most robust predictor of population recovery after a catastrophe. Aldrich and Meyer (2014) examined recent literature and evidence to investigate the critical role of social capital and networks in disaster recovery. They highlighted that disaster agencies, governmental decision makers, and NGOs need to strengthen social infrastructures at the community level to increase disaster resilience. Joshi and Aoki (2014) investigated two districts affected by the tsunami in India. They concluded that the strength of social networks, the commitment of residents to the community, popularity of leaders, and various social factors influenced the disaster recovery. Grube and Storr (2014) studied how pre-disaster systems of self-governance support post-disaster recovery. They concluded that local knowledge and knowledge transfer are important in the recovery of disaster-affected communities. To increase community resilience after a catastrophe, the role of social media is substantial.

2.2. *The role of social media in a disaster*

The importance of social media engagements after a disaster has been identified by many scholars (Kim & Hastak, 2017; Middleton et al., 2014; Poorazizi, Hunter, & Steiniger, 2015; Reuter, Heger, & Pipek, 2013; Yin et al., 2015; Yoo, Rand, Eftekhar, & Rabinovich, 2016). Social media has a range of roles, from preparing and receiving disaster preparedness information and warnings, and signaling and detecting disasters prior to an event, to linking community members following a disaster (Houston et al., 2015).

After the 2010 Haiti earthquake, people shared numerous texts and photos via social media. Within 48 h, the Red Cross had received US$8 million in donations, and this exemplified one benefit of the powerful information propagation capability of social media sites (Gao, Barbier, & Goolsby, 2011; Keim & Noji, 2011; Yates & Paquette,2011). Graham, Avery, and Park (2015) surveyed more than 300 local government officials from municipalities across the U.S. Their study identified that the extent of social media use is related with assessments of the local city's ability to control a crisis. It is also related to their overall evaluations of the strength of their responses. The Federal Emergency Management Agency (FEMA) utilizes various social media, including Facebook, Twitter, Instagram, LinkedIn and YouTube, to provide the public with emergency information related to a catastrophe (FEMA, 2016).

Yoo et al. (2016) collected Twitter data during Hurricane Sandy and applied information diffusion theory to characterize diffusion rates. The variables are (1) information cascade's diffusion speed, (2) cascade originator's influence and cascade content's contribution to situational awareness, (3) lateness in the launch of the cascade during the disaster, (4) incidence of cascade boosts by the originator, and (5) misleading cascade. They identified that internal diffusion through social media networks advances at a higher speed than information in these networks coming from external sources.

Furthermore, uses of social media as an information diffuser should be calibrated to expedite the effectiveness in an emergency. Keim and Noji (2011) emphasized that P2P communications could spread misinformation and rumor as well as privacy rights violations. An extremely high volume of messages via social media makes it hard for disaster-affected communities and professional emergency responders/agencies to process and analyze the information. Imran et al. (2013) proposed a system integrated with machine learning techniques to provide actionable information from social media. Liu et al. (2014) studied disaster information forms (social media vs. traditional media) and sources (national agencies and media vs. local agencies and media) to generate desired public outcomes such as intentions to seek and share emergency information.

2.3. *Social network analysis and tools*

Software and tools have been developed to fulfill the increasing need for social network data mining and visualization technology. Researchers created toolkits from sets of network analysis components

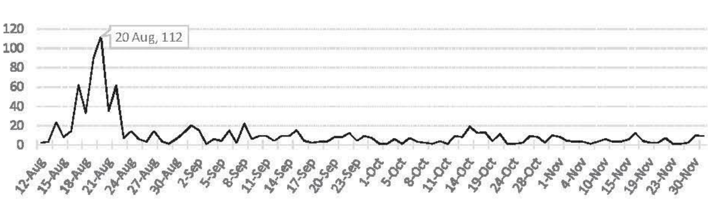


Fig. 5. Numbers of reactions on the Facebook page of the city of Baton Rouge.

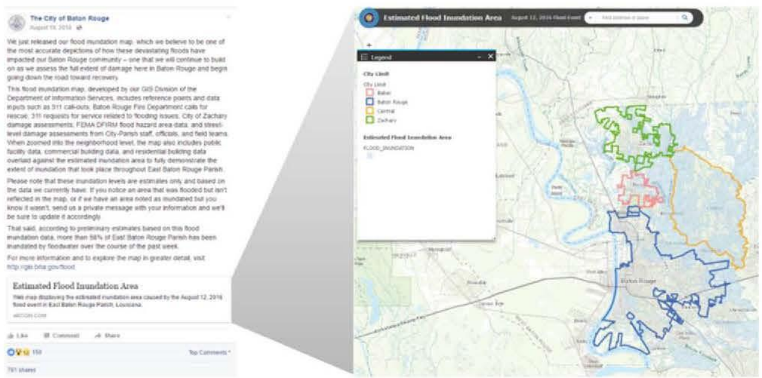


Fig. 6. Most shared and commented information on Facebook after the flood (eBRGIS, 2016).
(150 likes, 791 shares and 61 comments retrieved from the Facebook page of the city of Baton Rouge).

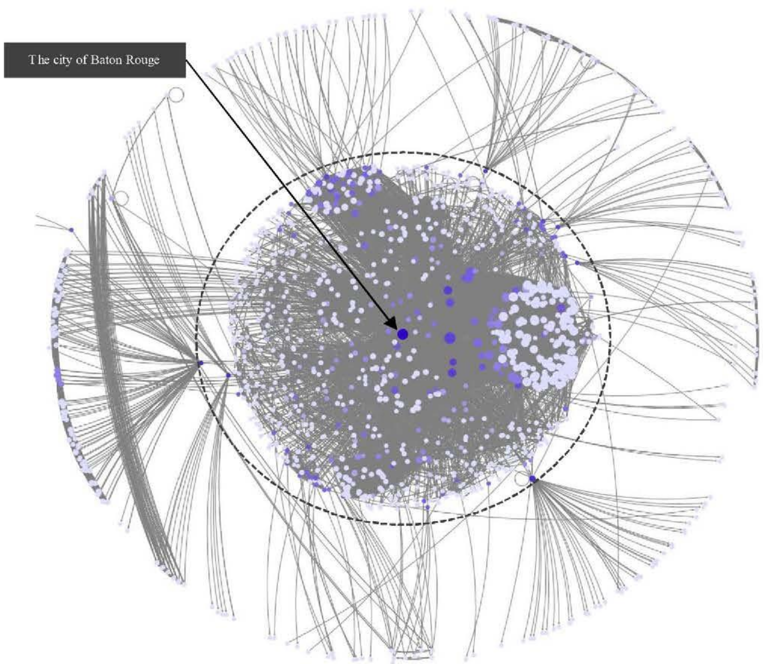
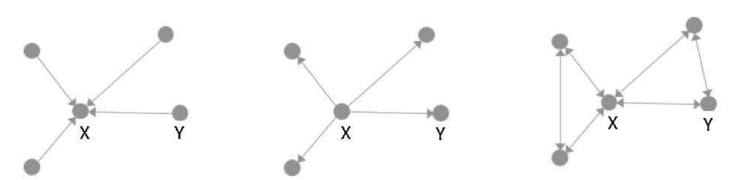


Fig. 7. Network graph during the 2016 Louisiana flood.
(Harel–Karen layout is used. Vertex size is based on out-degree. Bluer vertices represent higher betweenness)

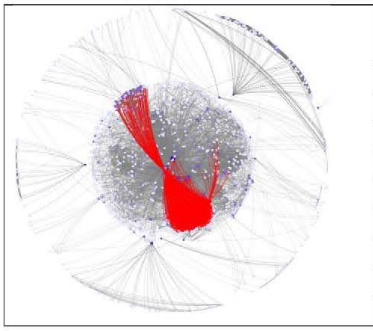


(a): In-degree centrality: X > Y (b): Out-degree centrality: X > Y (c) Betweenness centrality: X > Y

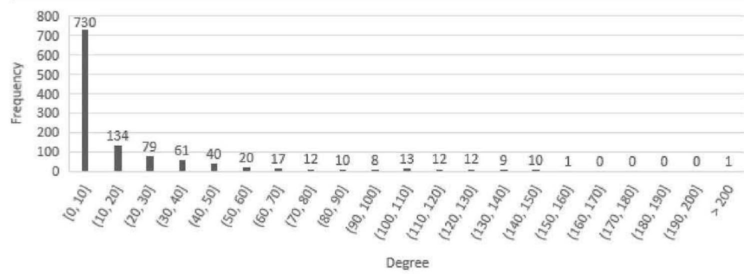
Fig. 8. Illustration of degree centrality.

not limited to R and the SNA library, JUNG, Guess, and Prefuse including NodeXL and Gephi (Adar, 2006; Heer, Card, & Landay, 2005; Smith et al., 2009; White, 2005). These tools have different characteristics, but most of them allow (1) computation of metrics that provide a local (actor level) and global (network level) description of the network, (2) graphical visualization of the network, and (3) community detection (Combe, Largeron, Egyed-Zsigmond, & Géry, 2010; Oliveira & Gama, 2012).

Table 3
Top 10 out-degree centrality and degree distribution.
Red-colored lines are all edges linked with top 10 out-degree vertices excluding CBR.



Users	Out-degree
CBR	228
User#1	153
User#2	150
User#3	149
User#4	147
User#5	147
User#6	146
User#7	145
User#8	144
User#9	143



(minimum 0, maximum 228, average 19, median 5).

3. Research objectives

Many studies have explored social media data to understand social networks and extract critical information to develop a pre- and post-disaster mitigation plan. This study explored disaster responses in social media after the 2016 Louisiana flood. The prolonged rainfall in southern parts of Louisiana resulted in catastrophic flooding that submerged thousands of houses and businesses. It was recorded as the worst disaster in the U.S. after Hurricane Sandy in 2012, and it damaged more than 60,000 homes (Ball, 2016; Brown et al., 2016; May & Bowerman, 2016; Yan & Flores,2016). This study applies SNA to convert social media data into knowledge. It provides insights to understand the critical role of social media for emergency information propagation. Objectives of this study are as follows:

1) Collect social media data from the Facebook page of the city of Baton Rouge during the period of the 2016 Louisiana flood, August 12–December 1, 2016.
2) Explore connections and patterns created by the aggregated interactions in the Facebook page during disaster responses.
3) Identify and analyze social roles and key players in the social network.
4) Analyze the posts during the disaster, such as discussions, top words and word pairs.
5) Suggest further actions to improve the effectiveness of information diffusion via social media.

4. Louisiana flood and social media

4.1. *Search-term trends: 2012 Hurricane Sandy vs. 2016 Louisiana flood*

The major media has been criticized by many leaders in Louisiana for the lack of coverage of the 2016 Louisiana flood, especially compared to the other major natural disasters in the U.S. (Berman, 2016; May & Bowerman, 2016; Pallotta, 2016; Scott, 2016). During the period, the media mainly covered the 2016 U.S. presidential election and the 2016 Rio Summer Olympics. Craig Fugate, the administrator for the FEMA, stated: "You have Olympics, you got the election. If you look at the national news, you're probably on the third or fourth page. … We think it is a national headline disaster" (O'Donoghue, 2016). For instance, the *New York Times* published its first story on the evening of August 14 (Hersher, 2016).

Thus, we explored Google Trends to identify 2012 and 2016 trending stories in the U.S. near two disasters: Hurricane Sandy and the Louisiana flood. The trend data, *interest over time*, are scaled on a range of 0–100 based on a topic's proportion to searches for all topics (Google, 2017).

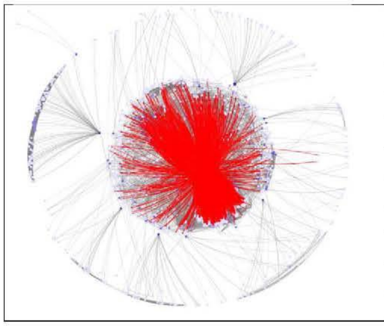
4.1.1. *Trends at a national level*

It was hard to observe the search-term trend (or interest over time) for *Louisiana flood 2016* compared to *2016 presidential election* and *2016 Rio Summer Olympics* at a national level. However, search-term trends in 2012 were different in similar circumstances when Hurricane Sandy struck. Despite the 2012 London Summer Olympics and the 2012 presidential election occurring in the year of Hurricane Sandy, media interest in Hurricane Sandy was significantly higher than in these other events. Hurricane Sandy hit New York City on Oct 29, 2012. Interest peaked during the week of October 28–November 3 (Fig. 2).

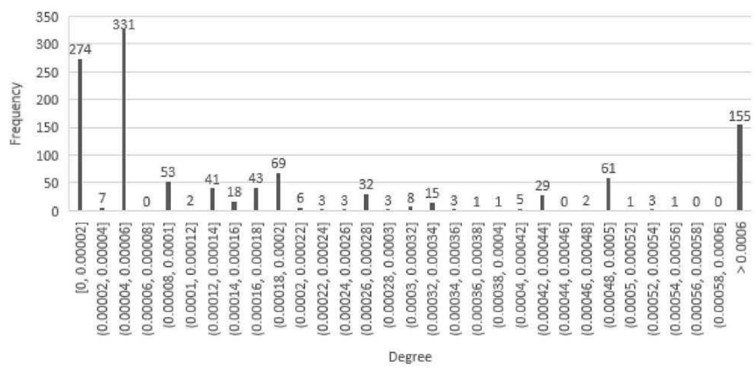
4.1.2. *Trends at a local level*

Google search-term trends in Louisiana are shown in Fig. 3. *Louisiana flood 2016* reached a peak during the week of Aug 17–21, 2016. Compared to Hurricane Sandy in 2012, the peak of interest on the topic, *2016 Louisiana flood,* was not higher than *2016 Rio Olympics* and

Table 4
Top 10 Eigenvector centrality and degree distribution.
Red-colored lines are all edges linked with top 10 in-degree vertices excluding CBR. User#5 is in both the top 10 out-degree and eigenvector centralities.



Users	Eigenvector
CBR	0.006628
User#10	0.006238
User#11	0.006149
User#12	0.006122
User#13	0.006084
User#14	0.00606
User#15	0.006042
User#16	0.006006
User#5	0.005995
User#18	0.005995



(minimum 0, maximum 0.00663, average 0.00085, median 0.00005)

2016 presidential election in Louisiana. Also, it reached the peak after the flood occurred in Aug 12, 2016.

4.2. Comparison of social media platforms: Facebook and Twitter

According to Social Times, Facebook has 1.59 billion monthly active users (as of Dec 2015), while Twitter has 320 million (as of March 2016) (Social Times, 2016). Duggan (2015) examined Facebook and Twitter users among internet users in the survey and identified Facebook as having a broader range of generation than Twitter. In addition, 70% of Facebook users are on the platform on a daily basis, compared with 38% of Twitter users (see Table 1). The Pew Research Center (2017) reported Facebook as the most widely used of the major social media platforms, and its user base is broadly representative of the population as a whole. In January 2016, 68% of U.S. adults were Facebook users.

The city of Baton Rouge has been using two social media platforms, Facebook and Twitter, since 2011. As of December 1, 2016, the number of Twitter followers was higher than Facebook followers, at 13,500 and 9936, respectively. However, Facebook user engagement was apparently higher than Twitter during the 2016 Louisiana flood. For example, a single post on the Facebook page was, on average, shared by 792 users and liked by 150 users, compared to posts on Twitter receiving 4–5 retweets and 1–2 likes.

5. Data collection and pre-processing

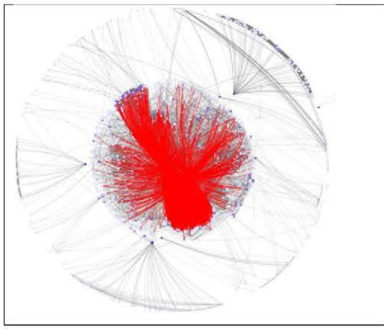
We collected data from the Facebook page of the city of Baton Rouge (www.facebook.com/cityofbatonrouge) that were created during August 12–December 1, 2016. There were 1171 users and 21,115 activities or responses on the page. To represent the collected data on a network graph, a vertex is defined as an engaged user and an edge is defined as a connection between users created by their interactions (see Fig. 4). We assumed any link between two vertices, regardless of direction, to be an indication of their similarity (Clauset, Newman, & Moore, 2004).

We filtered the collected data to ensure they were strictly related to the 2016 Louisiana flood before analyzing and visualizing the network. There were repeated vertex pairs on the edges, and 6400 edges with duplicates out of 27,515 edges (see Table 2) These duplicate vertex pairs may occur when user A replies to user B on multiple occasions. These duplicates can cause some metrics, such as *degree*, to be inaccurate (Smith et al., 2009). Thus, the 6400 edges were combined into a single weighted edge. Finally, edges that connect a vertex with itself − self-loops, of which there were 671–were deleted.

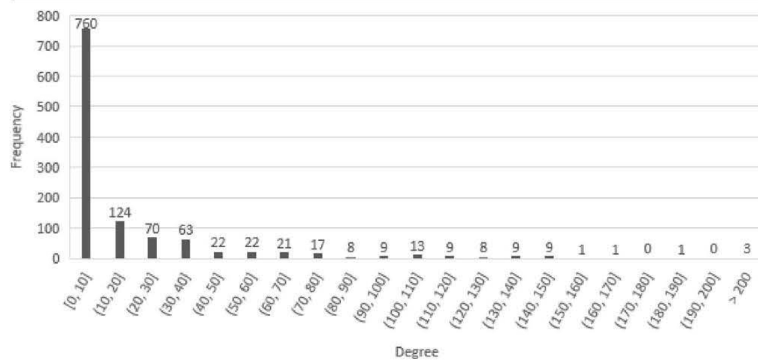
6. Results

The number of user engagements (e.g., comments, commented comments and user tagged) on the Facebook posts is described in Fig. 5. The number of user engagements exponentially increased and then declined after August 20. From August 24, the numbers were less than

Table 5
Top 10 in-degree centrality and degree distribution.
Red-colored lines are all edges linked with top 10 in-degree vertices excluding CBR.



Users	In-degree
CBR	829
User#19	296
User#20	254
User#21	252
User#22	184
User#23	169
User#24	159
User#25	148
User#26	146
User#27	145



(minimum 0, maximum 829, average 19.99, median 4.00).

20 (the trend is similar to that observed in the local search-term trend in Fig. 3).

The most shared and commented post was the estimated flood inundation map developed by the GIS division of the Department of Information Services in the city of Baton Rouge (see Fig. 6). The estimated flood inundation map was powered by a compilation of various data inputs including 911 call-outs, Baton Rouge Fire Department search-and-rescue data, City-Parish staff and other public officials, NOAA imagery, Civil Air Patrol imagery and FEMA DRIRM flood hazard areas (eBRGIS, 2016). The post consisted of text information with a link to the GIS map. Facebook users commented on the post to inform of incorrect information on the flood inundation map. Compared to the post on the city's Facebook page, there were 39 retweets and 18 likes on the Twitter post.

6.1. Network graph and structure

In social network analysis, graph-theoretic concepts are used to understand and analyze social phenomena (Ackland, 2010; Borgatti, Everett, & Johnson, 2013; Brandes, 2001; Wasseman & Faust, 1994). In Fig. 7, the graph is directed and laid out using the Harel–Koren fast multiscale layout algorithm (Harel & Koren, 2000). There are 1171 vertices, 21,115 edges, and 18 connected components. The vertex color is betweenness centrality and the size is scaled out-degree centrality. Maximum geodesic distance (diameter) is 5.00 and the average is 2.40 (see Table 2) The city of Baton Rouge is in the center of the network. The center of the network in the black-dashed circle is very dense with numerous vertices and edges. There are several vertices near the black-dashed circle that connect with other vertices at the outside of the network.

6.2. Degree centrality

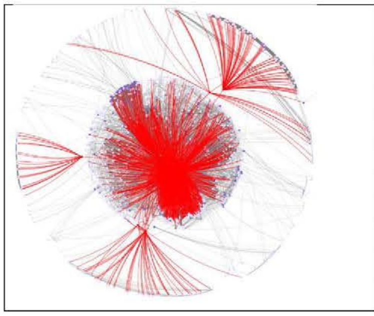
Degree centrality refers to the number of edges a vertex has to other vertices. As shown in Fig. 8, in-degree is the number of incoming edges incident to the vertex and out-degree is the number of outgoing edges incident to the vertex. Betweenness quantifies the number of times a vertex acts as a bridge along the shortest path between two other vertices (Freeman, 1977).

We analyze four types of degree centrality. The city of Baton Rouge has the highest out-degree, in-degree, eigenvector and betweenness centrality in the network. Most vertices at the core of the network are identified as individuals. There are no organizations or agencies in the top 10 centralities. The results below describe individual users actively involved in this emergency information propagation.

Out-degree, in-degree, and betweenness degree distribution are highly right-skewed. It represents a significant majority of vertices having a low degree, but a few vertices having a high degree as a hub in the network (Tables 3–5).

The six organizations/agencies including the city of Baton Rouge are ranked in the top 10 of betweenness centrality. The verticies with high betweenness play critical roles in the network structure. From the social network perspective, Wasseman and Faust (1994) described the importance of high betweenness: "interactions between two non-adjacent actors might depend on other actors in the set of actors, especially the actors who lie on the paths between the two." These are

Table 6
Top 10 betweenness centrality and degree distribution.
Red-colored lines are all edges linked with top 10 betweenness centrality vertices excluding CBR.



Users	Betweenness
CBR	1,082,218
Organization#1	166,500
Organization#2	81,549
Organization#3	49,982
User#19	31,711
User#20	29,937
User#21	26,838
Organization#4	22,838
Organization#5	20,572
User#22	13,791

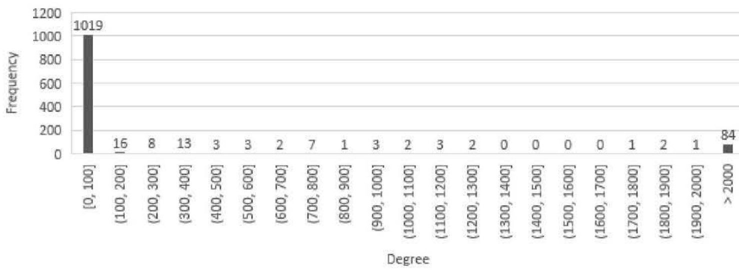


Table 7
Top 10 largest communities in the social network.

Rank	Size	Description
G1	144	Flood inundation map, information of debris separation, shelter locations
G2	63	Commenters on the flood inundation map – e.g., map update requests and sharing map information
G3	43	Donations and supports
G4	40	Road conditions (road closed/open)
G5	34	Locations of debris removal, debris collection status map
G6	33	Ordinances to help Baton Rouge residents; housing, noise ordinance waivers, waiving permit fees for structures damaged, policy changes
G7	30	Debris separation, Louisiana Department of Environmental Quality
G8	28	Reactors to hiring workers to help with debris removal efforts
G9	16	Commenters on the debris removal hiring event
G10	15	City events after final debris collection

also called *gatekeepers*, since they tend to control the information flow between communities (Oliveira & Gama, 2012). For example, a Facebook user in Texas shared a message to inform of the 2016 Louisiana flood via his Facebook page, encouraging people to help disaster recovery in the city of Baton Rouge. A network graph clearly describes a role of the vertices with highest betweenness centrality (see Table 6). Of the vertices in the network, 87% have betweenness centrality below 100. Thus, these high betweenness vertices played a role of gatekeepers in handling emergency information flow between the city of Baton Rouge and other communities.

6.3. *Community structure*

Most social networks tend to show *community structure*. This feature generally arises as a consequence of both global and local heterogeneity of edges distribution (Oliveira & Gama, 2012). We identified a community structure of the social network by the *Girvan–Newman algorithm* (Girvan & Newman, 2002; Newman & Girvan,2004). In Table 7, we provide an informal description of the 10 largest groups, which account for about 38% of the entire network. The remainder is generally divided into small, densely connected groups that represent highly specific co-interests of disaster-related information – e.g., flood inundation map, debris removal, road condition, donation and support. Interactions between groups are straightforwardly visualized in the graph (see Fig. 9). The interactions between groups have two types: (1) direct interactions and (2) indirect interactions. For example, G1 and G4 are directly connected, and the small groups (vertices in the red box) have a role as a bridge connecting G1 with G2.

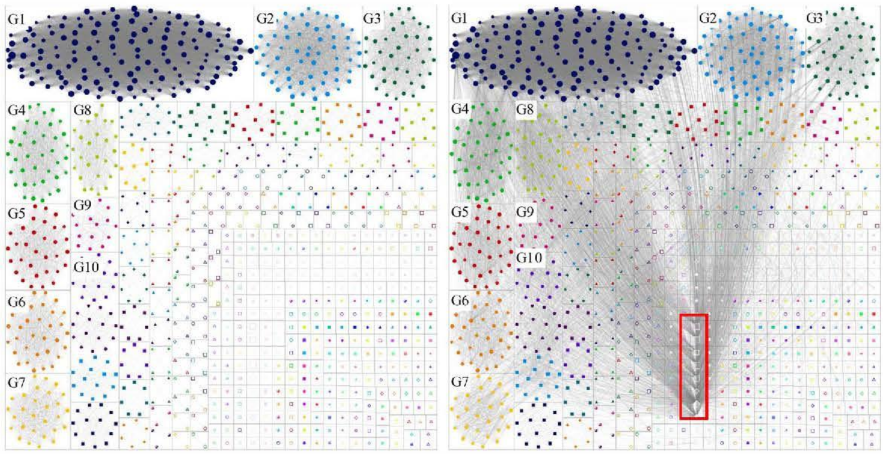
6.4. *Top words and word pairs*

Text analysis identified 77% of the posts during emergency responses as having positive words. The top five words during disaster responses are *map*, *water*, *thanks*, *GIS* and *flooded* (Table 8).

Top word pairs are listed in Table 9. The city of Baton Rouge operated a GIS flood map and shared the map with people. Most word pairs are related to flood, disaster recovery team and disaster debris removal in the city. There was a particular word pair, *private – message*, because people shared their home addresses via private messages to request rapid debris removal near their houses.

7. Conclusion

We investigated the Facebook social network in the city of Baton Rouge after the 2016 Louisiana flood. The data were collected from the city's Facebook page and analyzed for the emergent network after the flood. The city of Baton Rouge used both Twitter and Facebook to share



Community structure *Interactions between communities*

The primary divisions of community structure detected by the Girvan–Newman algorithm indicated by different vertex shapes and colors. Vertices in the red box played a role as a hub connecting G1 and G2.

Fig. 9. Community structure on the Facebook page of the city of Baton Rouge.

Table 8
Top Words in Tweets in Entire Graph.

Top Words in Tweets in Entire Graph	Count
Words in Sentiment List#1: Positive	4039
Words in Sentiment List#2: Negative	1206
Non-categorized Words	236,268
Total Words	241,513
Map	3395
Water	3265
Thanks	3090
GIS	2386
Flooded	2371

Table 9
Top word pairs.

Word Pairs	Count
GIS team	1698
private, message	462
water, house	456

emergency information. Facebook user engagement was higher than Twitter during the emergency responses. The trend of Facebook engagement significantly increased in the first two weeks, reached its peak on August 20, and then declined over time. We found that 47% of the engagements were generated within the first two weeks.

Statistical measures in the SNA provided insights about the structure of the network. We measured out-degree, in-degree, eigenvector and betweenness centrality in the emergent social network to identify the prominence or importance of vertices in the network. The degree distributions are very heterogeneous and highly right skewed (a large majority of vertices have a low degree but a small number of vertices have a high degree). Thus, we identified that there are certain vertices as a hub in the social network. We ranked top 10 out-degree, in-degree, eigenvector and betweenness centralities. The results suggested that individuals and agencies/organizations have different roles in social networks during emergency responses. The top 10 out-degree, in-degree and eigenvector centralities were individuals rather than emergency agencies/organizations, excluding the city of Baton Rouge. They actively shared emergency information with their online friends by either tagging their friends, posting a comment, or sharing information with their online community. Some vertices did not belong to either of the top 10 out-degree or in-degree centralities. Types of individual engagement in the social network are: (1) *like a post* (76.56%), (2) *write a comment* (15.55%) and (3) *share a post* (7.99%).

However, the top three betweenness centralities, with the exception of the city of Baton Rouge, were organizations/agencies, and six organizations were ranked in top 10 of betweenness centrality. We identified that organizations/agencies played a critical role in connecting a network of the city of Baton Rouge with external social groups or online communities.

The network graphs visualized the statistical analysis by the Harel–Koren fast multiscale algorithm in Section 6. The network graphs represented metrics to convey the result of the analysis. As shown in Fig. 7, the city of Baton Rouge was at the center of network as a hub and it is strongly linked with other vertices, i.e., individuals. It was the core of the entire network, as described in the graph. Organizations and agencies are at the periphery of the core network, but played a critical role in connecting external vertices with the core network. The social network graph has a similar structure to the conceptual diagram of social capital shown in Fig. 1; the core of a community consists of numerous individuals, while agencies and organizations link communities.

Text analysis from the Facebook posts identified that two-thirds of users left positive comments and feedback on the Facebook posts, with one-third leaving negative posts. Top word pairs were *GIS–team, flood–water* and *private–message*.

8. Discussion

We compared search-term trends about the 2016 Louisiana flood and Hurricane Sandy of 2012. There were summer Olympic Games and presidential elections around the time of both disasters, but the trends were significantly different. People's interest in the 2016 Louisiana flood was not significant and was lower than that shown for the summer Olympic Games and the presidential election, even though it was recorded as the worst disaster after Hurricane Sandy. As discussed in Section 4, there were articles criticizing the major media for a lack of coverage of the 2016 Louisiana flood. Further investigations are needed to answer how these events (Olympics and elections) affect information diffusion during disaster responses. Comparing the effectiveness of social media as early warning systems would be beneficial.

Contrary to previous studies, this case study showed that disaster-related information was diffused actively via Facebook rather than Twitter. There might be several reasons behind this. Firstly, Facebook has more functions for sharing numerous types of message via its interface, such as images, videos, and hyperlinks. This flexibility might help users understand information faster and trigger them to share multiple types of information with others. In addition, Facebook has 1.59 billion users (as of Dec 2015), which is about four times higher than Twitter (320 millions, as of March 2016) (Social Times, 2016). Duggan (2015) identified that of Facebook's total number of users, 70% visit the platform daily, while for Twitter this is 38%. Thus, more people might have a chance of being engaged in emergency information via Facebook rather than Twitter. Further investigations, using survey and interview, would identify their motivations and reasons for their engagements.

There was a limitation on data collection. Since we collected data from a Facebook fanpage of the city of Baton Rouge, we were not able to explore how the shared information on a user's Facebook page will be re-shared with other social networks, compared to a *retweet* on Twitter. This would enable us to precisely measure information diffusion across the community structure of social media. Also, the network is limited to Facebook, so it does not include other online and offline networks created during disaster responses.

It is critical for the public to receive accurate, reliable and timely information from emergency agencies during disasters. Many literatures identified that social media 1) influences social consciousness, 2) leads rapid information delivery, and 3) reach a broader and more targeted population than any conventional methods(Mohammadi et al., 2016). Thus, social media such as Twitter and Facebook is expected as a powerful tool for rapid information diffusion in emergency.

As our findings reveal, SNA could be applied to understand characteristics of online social network and structure in depth including critical central and intermediate vertices in the network. The results can be used to understand heterogeneity in social networks and applied to accelerate information diffusion in emergency. Thus, emergency agencies need to equip a network analysis tool and database to analyze local-, state- and national level social network in emergency. Also, a collaboration with social media such as Facebook and Twitter will be beneficial to improve reliability of data collection, monitor real-time data, and expedite the overall SNA process in emergency.

As discussed in Section 7, organizations with high betweenness centrality play a critical role to connect online communities in a social network. Thus, emergency agencies have an online partnership with public and private sector including NGOs and NPOs to create stronger bonds in their social network.

A future study is needed for understanding characteristics and effectiveness of different social media platform including Twitter, Facebook, Google+, YouTube and Instagram in disaster responses such as their feasibility and reliability as an information diffuser in emergency. Most questions could be answered by a multi-case study approach that would compare the use and effectiveness of social media across a broad range of disasters. Another future study is also needed for isolated vertices where information might not be reached via an existing online network. Therefore, application of search and location-based advertising services for emergency information is a crucial research topic to improve online information diffusion performance.

Acknowledgement

We are thankful to Dr. Natalie Lambert at the Brian Lamb School of Communication at Purdue University for her invaluable guidance and encouragement during this data collection and analysis.

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International Journal of Information Management 38 (2018) 86–96

Contents lists available at ScienceDirect

International Journal of Information Management

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

Research Note

Social network analysis: Characteristics of online social networks after a disaster

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ARTICLE INFO

Keywords:
Emergency information
Disaster communication
Social media
Disaster response
Social network analysis (SNA)

ABSTRACT

Social media, such as Twitter and Facebook, plays a critical role in disaster management by propagating emergency information to a disaster-affected community. It ranks as the fourth most popular source for accessing emergency information. Many studies have explored social media data to understand the networks and extract critical information to develop a pre- and post-disaster mitigation plan.

The 2016 flood in Louisiana damaged more than 60,000 homes and was the worst U.S. disaster after Hurricane Sandy in 2012. Parishes in Louisiana actively used their social media to share information with the disaster-affected community – e.g., flood inundation map, locations of emergency shelters, medical services, and debris removal operation. This study applies social network analysis to convert emergency social network data into knowledge. We explore patterns created by the aggregated interactions of online users on Facebook during disaster responses. It provides insights to understand the critical role of social media use for emergency information propagation. The study results show social networks consist of three entities: individuals, emergency agencies, and organizations. The core of a social network consists of numerous individuals. They are actively engaged to share information, communicate with the city of Baton Rouge, and update information. Emergency agencies and organizations are on the periphery of the social network, connecting a community with other communities. The results of this study will help emergency agencies develop their social media operation strategies for a disaster mitigation plan.

1. Introduction

Social media, such as Twitter and Facebook, plays a critical role in disaster management. It is ranked as the fourth most popular source for accessing emergency information (Lindsay, 2011). Mickoleit (2014) identified that government institutions are using platforms such as Twitter, Facebook, and blogs to communicate with their communities. Twitter accounts have been created in 24 out of 34 OECD member countries, which can be compared to 21 out of 34 for Facebook. Many studies have explored the systematic use of social media during emergency responses by extracting social media data to identify needs of a disaster-affected community (Imran, Elbassuoni, Castillo, Diaz, & Meier, 2013; Yin et al., 2015). For example, social media data was used to develop a GIS-based real-time map during 2012 Hurricane Sandy in NYC. It shared emergency information and community needs with emergency agencies and NGOs (Middleton, Middleton, & Modafferi, 2014). Furthermore, real-time data from social media has been used to develop an early warning system for a tornado (Knox et al., 2013; Tyshchuk, Hui, Grabowski, & Wallace, 2011). Social media is used to communicate emergency information and urgent requests between emergency agencies and disaster-affected people (Feldman et al., 2016; Lindsay, 2011). These approaches support emergency agencies in understanding emerging situations rapidly after a disaster.

More than 60,000 homes were damaged in the 2016 flood in Louisiana (Han, 2016). It was the worst disaster after Hurricane Sandy in 2012 (Yan & Flores, 2016). A couple of parishes in Louisiana used their social media to share emergency information with people affected by the disaster. The city of Baton Rouge in Louisiana actively used its social media, such as Facebook and Twitter, to deliver real-time emergency information to the affected people in a timely manner. Few studies have analyzed social network structures and roles during disaster responses. This study applied social network analysis (SNA) to understand the characteristics of social media networks in Louisiana during emergency responses.

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http://dx.doi.org/10.1016/j.ijinfomgt.2017.08.003
Received 30 June 2017; Received in revised form 15 August 2017; Accepted 25 August 2017
Available online 22 September 2017

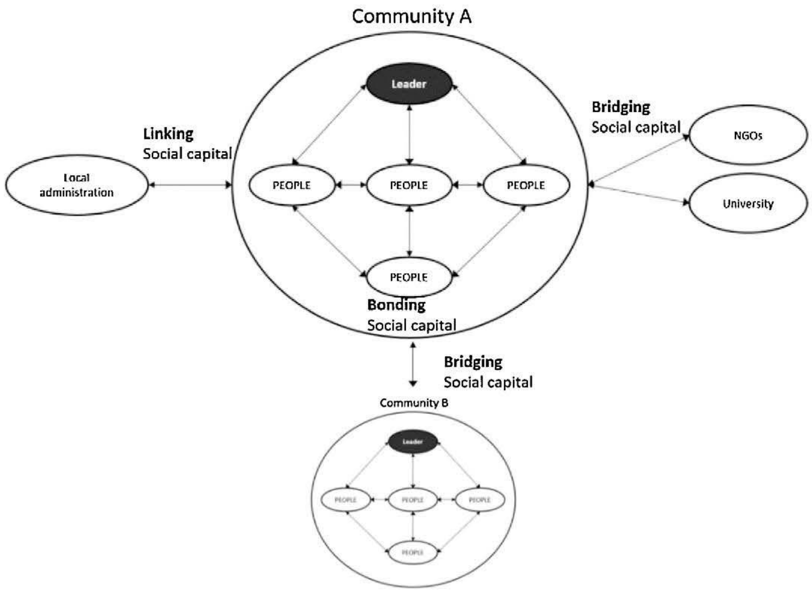


Fig. 1. Conceptual diagram of social capital (Nakagawa & Shaw, 2004).

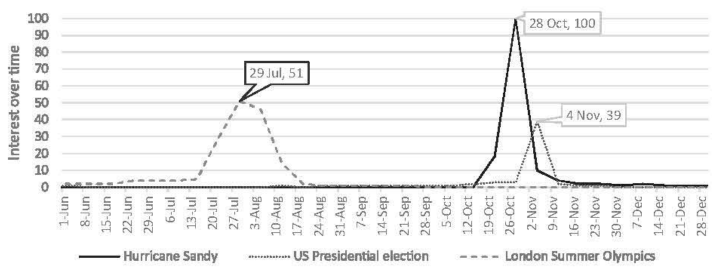


Fig. 2. Search-term comparison during 2012 Hurricane Sandy in the U.S. (Google Trends, 2017a).

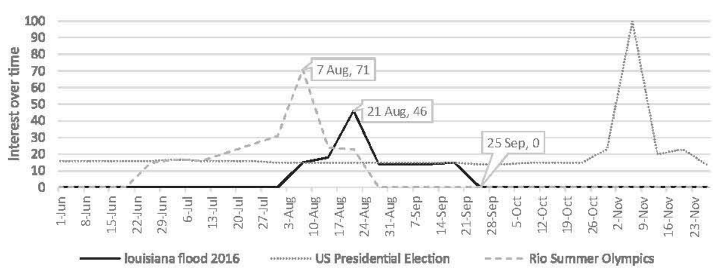


Fig. 3. Search-term comparison during 2016 Louisiana flood in the city of Baton Rouge, Louisiana, USA (Google Trends, 2017b).

2. Literature review

2.1. Social capital for disaster recovery

Social capital can be defined as “the resources accumulated through the relationships among people” (Coleman, 1988). Positive social outcomes from social capital have been identified through public health, lower crime rates, and financial markets (Adler & Kwon, 2002). In general, social capital brings a positive effect of interaction among participants in a social network (Helliwell & Putnam, 2004). Ellison, Steinfield, and Lampe (2007) identified that greater social capital

Table 1
Social media demographics and frequency (Duggan, 2015).

Facebook		Twitter
18–29	82%	32%
30–49	79%	29%
50–64	64%	13%
65+	48%	6%
Daily	70%	38%
Weekly	21%	21%
Less often	9%	40%

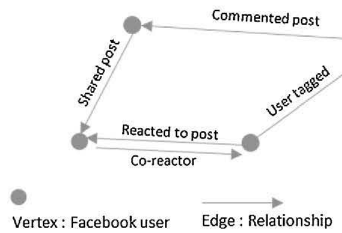


Fig. 4. Illustration of users and relationship.

Table 2
Overall Metrics.

Graph Metric	Value
Graph Type	Directed
Vertices	1171
Unique Edges	21,115
Edges with Duplicates	6400
Total Edges	27,515
Self-Loops	671
Reciprocated Vertex Pair Ratio	0.024
Reciprocated Edge Ratio	0.047
Connected Components	18
Single-Vertex Connected Components	16
Maximum Vertices in a Connected Component	1153
Maximum Edges in a Connected Component	27,510
Maximum Geodesic Distance (Diameter)	5
Average Geodesic Distance	2.41
Graph Density	0.02

increased commitment to a community and the ability to mobilize collective actions.

Many scholars have emphasized that social capital plays a critical role in responses to disasters. Nakagawa and Shaw (2004) examined the post-earthquake rehabilitation and reconstruction programs in two cases: Kobe in Japan and Gujarat in India. They identified that social capital and leadership in the community are the basic attributes for rapid disaster recovery. They described three aspects of social capital: *bonding*, *bridging* and *linking (see* Fig. 1). By investigating disaster recovery after the 1995 Kobe earthquake in Japan, Aldrich (2011) emphasized that the power of people (social capital) is the strongest and most robust predictor of population recovery after a catastrophe. Aldrich and Meyer (2014) examined recent literature and evidence to investigate the critical role of social capital and networks in disaster recovery. They highlighted that disaster agencies, governmental decision makers, and NGOs need to strengthen social infrastructures at the community level to increase disaster resilience. Joshi and Aoki (2014) investigated two districts affected by the tsunami in India. They concluded that the strength of social networks, the commitment of residents to the community, popularity of leaders, and various social factors influenced the disaster recovery. Grube and Storr (2014) studied how pre-disaster systems of self-governance support post-disaster recovery. They concluded that local knowledge and knowledge transfer are important in the recovery of disaster-affected communities. To increase community resilience after a catastrophe, the role of social media is substantial.

2.2. The role of social media in a disaster

The importance of social media engagements after a disaster has been identified by many scholars (Kim & Hastak, 2017; Middleton et al., 2014; Poorazizi, Hunter, & Steiniger, 2015; Reuter, Heger, & Pipek, 2013; Yin et al., 2015; Yoo, Rand, Eftekhar, & Rabinovich, 2016). Social media has a range of roles, from preparing and receiving disaster preparedness information and warnings, and signaling and detecting disasters prior to an event, to linking community members following a disaster (Houston et al., 2015).

After the 2010 Haiti earthquake, people shared numerous texts and photos via social media. Within 48 h, the Red Cross had received US$8 million in donations, and this exemplified one benefit of the powerful information propagation capability of social media sites (Gao, Barbier, & Goolsby, 2011; Keim & Noji, 2011; Yates & Paquette,2011). Graham, Avery, and Park (2015) surveyed more than 300 local government officials from municipalities across the U.S. Their study identified that the extent of social media use is related with assessments of the local city's ability to control a crisis. It is also related to their overall evaluations of the strength of their responses. The Federal Emergency Management Agency (FEMA) utilizes various social media, including Facebook, Twitter, Instagram, LinkedIn and YouTube, to provide the public with emergency information related to a catastrophe (FEMA, 2016).

Yoo et al. (2016) collected Twitter data during Hurricane Sandy and applied information diffusion theory to characterize diffusion rates. The variables are (1) information cascade's diffusion speed, (2) cascade originator's influence and cascade content's contribution to situational awareness, (3) lateness in the launch of the cascade during the disaster, (4) incidence of cascade boosts by the originator, and (5) misleading cascade. They identified that internal diffusion through social media networks advances at a higher speed than information in these networks coming from external sources.

Furthermore, uses of social media as an information diffuser should be calibrated to expedite the effectiveness in an emergency. Keim and Noji (2011) emphasized that P2P communications could spread misinformation and rumor as well as privacy rights violations. An extremely high volume of messages via social media makes it hard for disaster-affected communities and professional emergency responders/agencies to process and analyze the information. Imran et al. (2013) proposed a system integrated with machine learning techniques to provide actionable information from social media. Liu et al. (2014) studied disaster information forms (social media vs. traditional media) and sources (national agencies and media vs. local agencies and media) to generate desired public outcomes such as intentions to seek and share emergency information.

2.3. Social network analysis and tools

Software and tools have been developed to fulfill the increasing need for social network data mining and visualization technology. Researchers created toolkits from sets of network analysis components

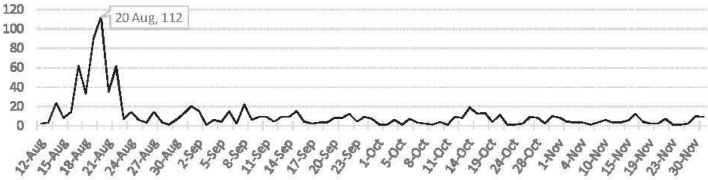


Fig. 5. Numbers of reactions on the Facebook page of the city of Baton Rouge.

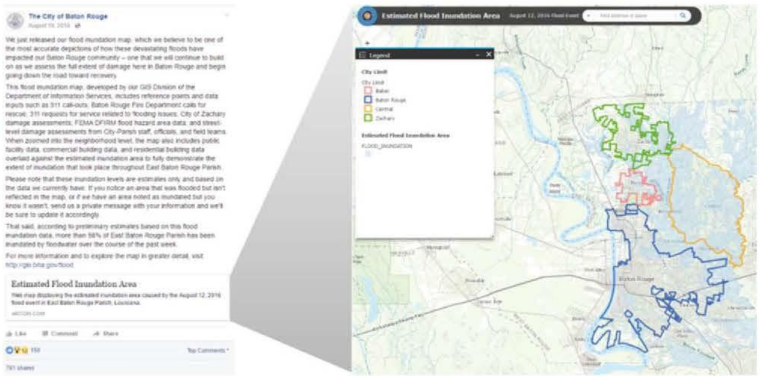


Fig. 6. Most shared and commented information on Facebook after the flood (eBRGIS, 2016).
(150 likes, 791 shares and 61 comments retrieved from the Facebook page of the city of Baton Rouge).

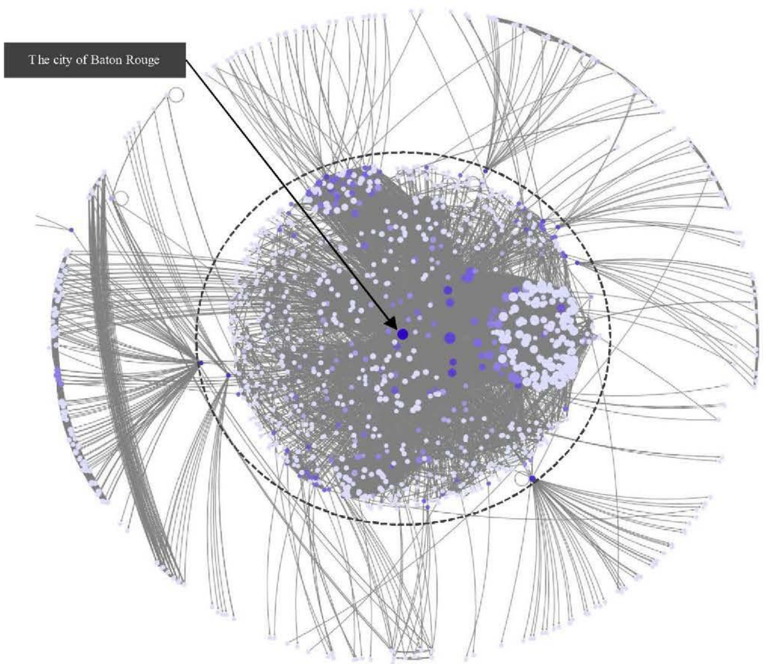
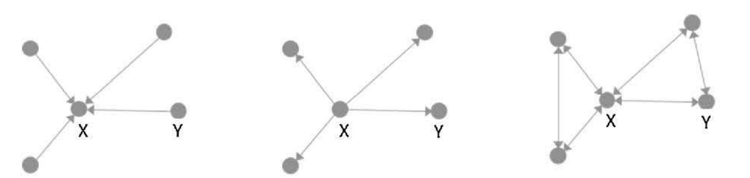


Fig. 7. Network graph during the 2016 Louisiana flood.
(Harel–Karen layout is used. Vertex size is based on out-degree. Bluer vertices represent higher betweenness)

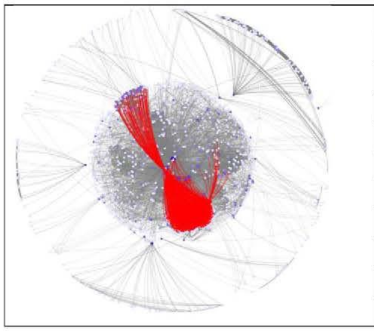


(a): In-degree centrality: X > Y *(b): Out-degree centrality: X > Y* *(c) Betweenness centrality: X > Y*

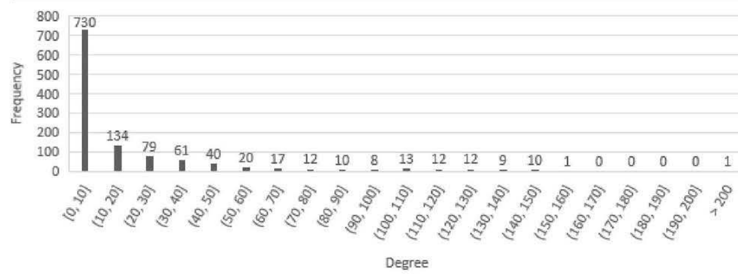
Fig. 8. Illustration of degree centrality.

not limited to R and the SNA library, JUNG, Guess, and Prefuse including NodeXL and Gephi (Adar, 2006; Heer, Card, & Landay, 2005; Smith et al., 2009; White, 2005). These tools have different characteristics, but most of them allow (1) computation of metrics that provide a local (actor level) and global (network level) description of the network, (2) graphical visualization of the network, and (3) community detection (Combe, Largeron, Egyed-Zsigmond, & Géry, 2010; Oliveira & Gama, 2012).

Table 3
Top 10 out-degree centrality and degree distribution.
Red-colored lines are all edges linked with top 10 out-degree vertices excluding CBR.



Users	Out-degree
CBR	228
User#1	153
User#2	150
User#3	149
User#4	147
User#5	147
User#6	146
User#7	145
User#8	144
User#9	143



(minimum 0, maximum 228, average 19, median 5).

3. Research objectives

Many studies have explored social media data to understand social networks and extract critical information to develop a pre- and post-disaster mitigation plan. This study explored disaster responses in social media after the 2016 Louisiana flood. The prolonged rainfall in southern parts of Louisiana resulted in catastrophic flooding that submerged thousands of houses and businesses. It was recorded as the worst disaster in the U.S. after Hurricane Sandy in 2012, and it damaged more than 60,000 homes (Ball, 2016; Brown et al., 2016; May & Bowerman, 2016; Yan & Flores,2016). This study applies SNA to convert social media data into knowledge. It provides insights to understand the critical role of social media for emergency information propagation. Objectives of this study are as follows:

1) Collect social media data from the Facebook page of the city of Baton Rouge during the period of the 2016 Louisiana flood, August 12–December 1, 2016.
2) Explore connections and patterns created by the aggregated interactions in the Facebook page during disaster responses.
3) Identify and analyze social roles and key players in the social network.
4) Analyze the posts during the disaster, such as discussions, top words and word pairs.
5) Suggest further actions to improve the effectiveness of information diffusion via social media.

4. Louisiana flood and social media

4.1. *Search-term trends: 2012 Hurricane Sandy vs. 2016 Louisiana flood*

The major media has been criticized by many leaders in Louisiana for the lack of coverage of the 2016 Louisiana flood, especially compared to the other major natural disasters in the U.S. (Berman, 2016; May & Bowerman, 2016; Pallotta, 2016; Scott, 2016). During the period, the media mainly covered the 2016 U.S. presidential election and the 2016 Rio Summer Olympics. Craig Fugate, the administrator for the FEMA, stated: “You have Olympics, you got the election. If you look at the national news, you’re probably on the third or fourth page. … We think it is a national headline disaster” (O’Donoghue, 2016). For instance, the *New York Times* published its first story on the evening of August 14 (Hersher, 2016).

Thus, we explored Google Trends to identify 2012 and 2016 trending stories in the U.S. near two disasters: Hurricane Sandy and the Louisiana flood. The trend data, *interest over time*, are scaled on a range of 0–100 based on a topic’s proportion to searches for all topics (Google, 2017).

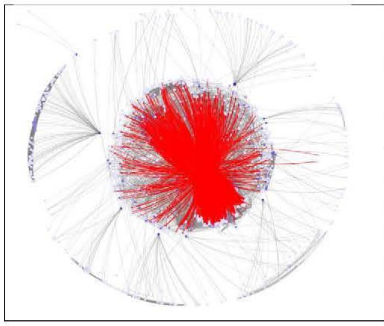
4.1.1. *Trends at a national level*

It was hard to observe the search-term trend (or interest over time) for *Louisiana flood 2016* compared to *2016 presidential election* and *2016 Rio Summer Olympics* at a national level. However, search-term trends in 2012 were different in similar circumstances when Hurricane Sandy struck. Despite the 2012 London Summer Olympics and the 2012 presidential election occurring in the year of Hurricane Sandy, media interest in Hurricane Sandy was significantly higher than in these other events. Hurricane Sandy hit New York City on Oct 29, 2012. Interest peaked during the week of October 28–November 3 (Fig. 2).

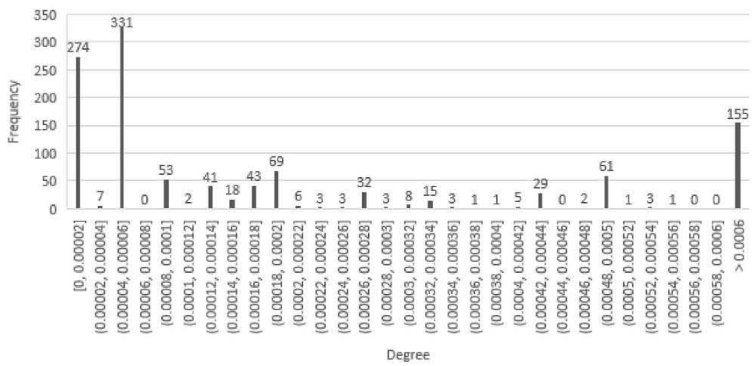
4.1.2. *Trends at a local level*

Google search-term trends in Louisiana are shown in Fig. 3. *Louisiana flood 2016* reached a peak during the week of Aug 17–21, 2016. Compared to Hurricane Sandy in 2012, the peak of interest on the topic, *2016 Louisiana flood*, was not higher than *2016 Rio Olympics* and

Table 4
Top 10 Eigenvector centrality and degree distribution.
Red-colored lines are all edges linked with top 10 in-degree vertices excluding CBR. User#5 is in both the top 10 out-degree and eigenvector centralities.



Users	Eigenvector
CBR	0.006628
User#10	0.006238
User#11	0.006149
User#12	0.006122
User#13	0.006084
User#14	0.00606
User#15	0.006042
User#16	0.006006
User#5	0.005995
User#18	0.005995



(minimum 0, maximum 0.00663, average 0.00085, median 0.00005)

2016 presidential election in Louisiana. Also, it reached the peak after the flood occurred in Aug 12, 2016.

4.2. Comparison of social media platforms: Facebook and Twitter

According to Social Times, Facebook has 1.59 billion monthly active users (as of Dec 2015), while Twitter has 320 million (as of March 2016) (Social Times, 2016). Duggan (2015) examined Facebook and Twitter users among internet users in the survey and identified Facebook as having a broader range of generation than Twitter. In addition, 70% of Facebook users are on the platform on a daily basis, compared with 38% of Twitter users (see Table 1). The Pew Research Center (2017) reported Facebook as the most widely used of the major social media platforms, and its user base is broadly representative of the population as a whole. In January 2016, 68% of U.S. adults were Facebook users.

The city of Baton Rouge has been using two social media platforms, Facebook and Twitter, since 2011. As of December 1, 2016, the number of Twitter followers was higher than Facebook followers, at 13,500 and 9936, respectively. However, Facebook user engagement was apparently higher than Twitter during the 2016 Louisiana flood. For example, a single post on the Facebook page was, on average, shared by 792 users and liked by 150 users, compared to posts on Twitter receiving 4–5 retweets and 1–2 likes.

5. Data collection and pre-processing

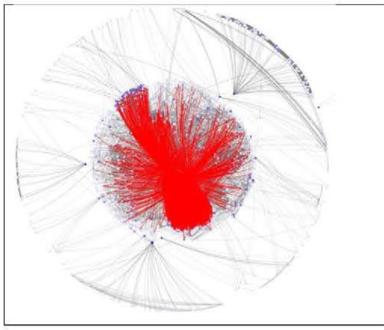
We collected data from the Facebook page of the city of Baton Rouge (www.facebook.com/cityofbatonrouge) that were created during August 12–December 1, 2016. There were 1171 users and 21,115 activities or responses on the page. To represent the collected data on a network graph, a vertex is defined as an engaged user and an edge is defined as a connection between users created by their interactions (see Fig. 4). We assumed any link between two vertices, regardless of direction, to be an indication of their similarity (Clauset, Newman, & Moore, 2004).

We filtered the collected data to ensure they were strictly related to the 2016 Louisiana flood before analyzing and visualizing the network. There were repeated vertex pairs on the edges, and 6400 edges with duplicates out of 27,515 edges (see Table 2) These duplicate vertex pairs may occur when user A replies to user B on multiple occasions. These duplicates can cause some metrics, such as *degree*, to be inaccurate (Smith et al., 2009). Thus, the 6400 edges were combined into a single weighted edge. Finally, edges that connect a vertex with itself − self-loops, of which there were 671–were deleted.

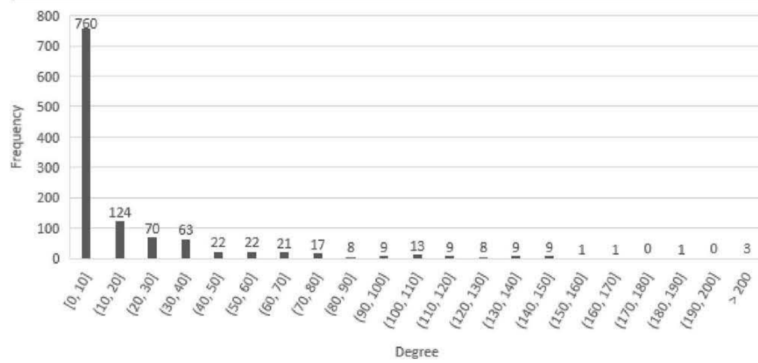
6. Results

The number of user engagements (e.g., comments, commented comments and user tagged) on the Facebook posts is described in Fig. 5. The number of user engagements exponentially increased and then declined after August 20. From August 24, the numbers were less than

Table 5
Top 10 in-degree centrality and degree distribution.
Red-colored lines are all edges linked with top 10 in-degree vertices excluding CBR.



Users	In-degree
CBR	829
User#19	296
User#20	254
User#21	252
User#22	184
User#23	169
User#24	159
User#25	148
User#26	146
User#27	145



(minimum 0, maximum 829, average 19.99, median 4.00).

20 (the trend is similar to that observed in the local search-term trend in Fig. 3).

The most shared and commented post was the estimated flood inundation map developed by the GIS division of the Department of Information Services in the city of Baton Rouge (see Fig. 6). The estimated flood inundation map was powered by a compilation of various data inputs including 911 call-outs, Baton Rouge Fire Department search-and-rescue data, City-Parish staff and other public officials, NOAA imagery, Civil Air Patrol imagery and FEMA DRIRM flood hazard areas (eBRGIS, 2016). The post consisted of text information with a link to the GIS map. Facebook users commented on the post to inform of incorrect information on the flood inundation map. Compared to the post on the city's Facebook page, there were 39 retweets and 18 likes on the Twitter post.

6.1. Network graph and structure

In social network analysis, graph-theoretic concepts are used to understand and analyze social phenomena (Ackland, 2010; Borgatti, Everett, & Johnson, 2013; Brandes, 2001; Wasseman & Faust, 1994). In Fig. 7, the graph is directed and laid out using the Harel–Koren fast multiscale layout algorithm (Harel & Koren, 2000). There are 1171 vertices, 21,115 edges, and 18 connected components. The vertex color is betweenness centrality and the size is scaled out-degree centrality. Maximum geodesic distance (diameter) is 5.00 and the average is 2.40 (see Table 2) The city of Baton Rouge is in the center of the network. The center of the network in the black-dashed circle is very dense with numerous vertices and edges. There are several vertices near the black-dashed circle that connect with other vertices at the outside of the network.

6.2. Degree centrality

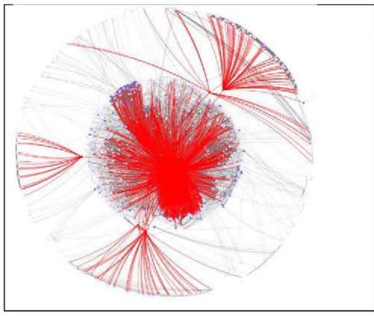
Degree centrality refers to the number of edges a vertex has to other vertices. As shown in Fig. 8, in-degree is the number of incoming edges incident to the vertex and out-degree is the number of outgoing edges incident to the vertex. Betweenness quantifies the number of times a vertex acts as a bridge along the shortest path between two other vertices (Freeman, 1977).

We analyze four types of degree centrality. The city of Baton Rouge has the highest out-degree, in-degree, eigenvector and betweenness centrality in the network. Most vertices at the core of the network are identified as individuals. There are no organizations or agencies in the top 10 centralities. The results below describe individual users actively involved in this emergency information propagation.

Out-degree, in-degree, and betweenness degree distribution are highly right-skewed. It represents a significant majority of vertices having a low degree, but a few vertices having a high degree as a hub in the network (Tables 3–5).

The six organizations/agencies including the city of Baton Rouge are ranked in the top 10 of betweenness centrality. The verticies with high betweenness play critical roles in the network structure. From the social network perspective, Wasseman and Faust (1994) described the importance of high betweenness: "interactions between two non-adjacent actors might depend on other actors in the set of actors, especially the actors who lie on the paths between the two." These are

Table 6
Top 10 betweenness centrality and degree distribution.
Red-colored lines are all edges linked with top 10 betweenness centrality vertices excluding CBR.



Users	Betweenness
CBR	1,082,218
Organization#1	166,500
Organization#2	81,549
Organization#3	49,982
User#19	31,711
User#20	29,937
User#21	26,838
Organization#4	22,838
Organization#5	20,572
User#22	13,791

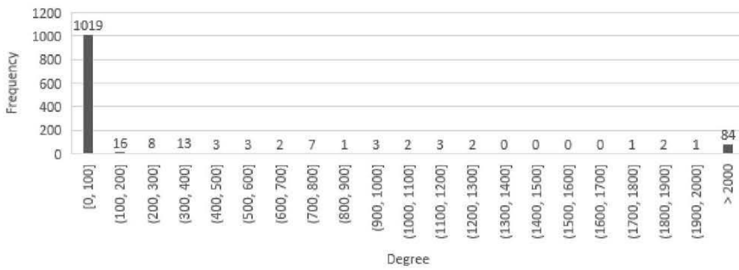


Table 7
Top 10 largest communities in the social network.

Rank	Size	Description
G1	144	Flood inundation map, information of debris separation, shelter locations
G2	63	Commenters on the flood inundation map – e.g., map update requests and sharing map information
G3	43	Donations and supports
G4	40	Road conditions (road closed/open)
G5	34	Locations of debris removal, debris collection status map
G6	33	Ordinances to help Baton Rouge residents; housing, noise ordinance waivers, waiving permit fees for structures damaged, policy changes
G7	30	Debris separation, Louisiana Department of Environmental Quality
G8	28	Reactors to hiring workers to help with debris removal efforts
G9	16	Commenters on the debris removal hiring event
G10	15	City events after final debris collection

also called *gatekeepers*, since they tend to control the information flow between communities (Oliveira & Gama, 2012). For example, a Facebook user in Texas shared a message to inform of the 2016 Louisiana flood via his Facebook page, encouraging people to help disaster recovery in the city of Baton Rouge. A network graph clearly describes a role of the vertices with highest betweenness centrality (see Table 6). Of the vertices in the network, 87% have betweenness centrality below 100. Thus, these high betweenness vertices played a role of gatekeepers in handling emergency information flow between the city of Baton Rouge and other communities.

6.3. Community structure

Most social networks tend to show *community structure*. This feature generally arises as a consequence of both global and local heterogeneity of edges distribution (Oliveira & Gama, 2012). We identified a community structure of the social network by the *Girvan–Newman algorithm* (Girvan & Newman, 2002; Newman & Girvan,2004). In Table 7, we provide an informal description of the 10 largest groups, which account for about 38% of the entire network. The remainder is generally divided into small, densely connected groups that represent highly specific co-interests of disaster-related information – e.g., flood inundation map, debris removal, road condition, donation and support. Interactions between groups are straightforwardly visualized in the graph (see Fig. 9). The interactions between groups have two types: (1) direct interactions and (2) indirect interactions. For example, G1 and G4 are directly connected, and the small groups (vertices in the red box) have a role as a bridge connecting G1 with G2.

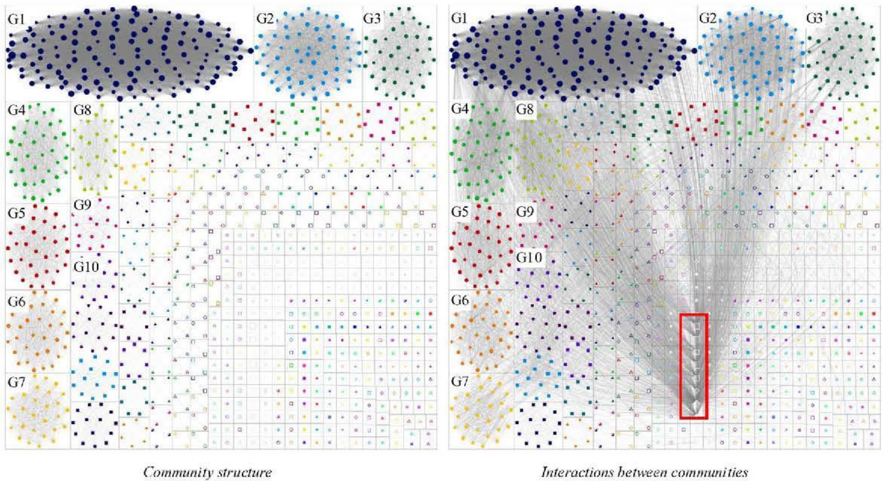
6.4. Top words and word pairs

Text analysis identified 77% of the posts during emergency responses as having positive words. The top five words during disaster responses are *map*, *water*, *thanks*, *GIS* and *flooded* (Table 8).

Top word pairs are listed in Table 9. The city of Baton Rouge operated a GIS flood map and shared the map with people. Most word pairs are related to flood, disaster recovery team and disaster debris removal in the city. There was a particular word pair, *private – message*, because people shared their home addresses via private messages to request rapid debris removal near their houses.

7. Conclusion

We investigated the Facebook social network in the city of Baton Rouge after the 2016 Louisiana flood. The data were collected from the city's Facebook page and analyzed for the emergent network after the flood. The city of Baton Rouge used both Twitter and Facebook to share



The primary divisions of community structure detected by the Girvan–Newman algorithm indicated by different vertex shapes and colors. Vertices in the red box played a role as a hub connecting G1 and G2.

Fig. 9. Community structure on the Facebook page of the city of Baton Rouge.

Table 8
Top Words in Tweets in Entire Graph.

Top Words in Tweets in Entire Graph	Count
Words in Sentiment List#1: Positive	4039
Words in Sentiment List#2: Negative	1206
Non-categorized Words	236,268
Total Words	241,513
Map	3395
Water	3265
Thanks	3090
GIS	2386
Flooded	2371

Table 9
Top word pairs.

Word Pairs	Count
GIS team	1698
private, message	462
water, house	456

emergency information. Facebook user engagement was higher than Twitter during the emergency responses. The trend of Facebook engagement significantly increased in the first two weeks, reached its peak on August 20, and then declined over time. We found that 47% of the engagements were generated within the first two weeks.

Statistical measures in the SNA provided insights about the structure of the network. We measured out-degree, in-degree, eigenvector and betweenness centrality in the emergent social network to identify the prominence or importance of vertices in the network. The degree distributions are very heterogeneous and highly right skewed (a large majority of vertices have a low degree but a small number of vertices have a high degree). Thus, we identified that there are certain vertices as a hub in the social network. We ranked top 10 out-degree, in-degree, eigenvector and betweenness centralities. The results suggested that individuals and agencies/organizations have different roles in social networks during emergency responses. The top 10 out-degree, in-degree and eigenvector centralities were individuals rather than emergency agencies/organizations, excluding the city of Baton Rouge. They actively shared emergency information with their online friends by either tagging their friends, posting a comment, or sharing information with their online community. Some vertices did not belong to either of the top 10 out-degree or in-degree centralities. Types of individual engagement in the social network are: (1) *like a post* (76.56%), (2) *write a comment* (15.55%) and (3) *share a post* (7.99%).

However, the top three betweenness centralities, with the exception of the city of Baton Rouge, were organizations/agencies, and six organizations were ranked in top 10 of betweenness centrality. We identified that organizations/agencies played a critical role in connecting a network of the city of Baton Rouge with external social groups or online communities.

The network graphs visualized the statistical analysis by the Harel–Koren fast multiscale algorithm in Section 6. The network graphs represented metrics to convey the result of the analysis. As shown in Fig. 7, the city of Baton Rouge was at the center of network as a hub and it is strongly linked with other vertices, i.e., individuals. It was the core of the entire network, as described in the graph. Organizations and agencies are at the periphery of the core network, but played a critical role in connecting external vertices with the core network. The social network graph has a similar structure to the conceptual diagram of social capital shown in Fig. 1; the core of a community consists of numerous individuals, while agencies and organizations link communities.

Text analysis from the Facebook posts identified that two-thirds of users left positive comments and feedback on the Facebook posts, with one-third leaving negative posts. Top word pairs were *GIS–team, flood–water* and *private–message*.

8. Discussion

We compared search-term trends about the 2016 Louisiana flood and Hurricane Sandy of 2012. There were summer Olympic Games and presidential elections around the time of both disasters, but the trends were significantly different. People's interest in the 2016 Louisiana flood was not significant and was lower than that shown for the summer Olympic Games and the presidential election, even though it was recorded as the worst disaster after Hurricane Sandy. As discussed in Section 4, there were articles criticizing the major media for a lack of coverage of the 2016 Louisiana flood. Further investigations are needed to answer how these events (Olympics and elections) affect information diffusion during disaster responses. Comparing the effectiveness of social media as early warning systems would be beneficial.

Contrary to previous studies, this case study showed that disaster-related information was diffused actively via Facebook rather than Twitter. There might be several reasons behind this. Firstly, Facebook has more functions for sharing numerous types of message via its interface, such as images, videos, and hyperlinks. This flexibility might help users understand information faster and trigger them to share multiple types of information with others. In addition, Facebook has 1.59 billion users (as of Dec 2015), which is about four times higher than Twitter (320 millions, as of March 2016) (Social Times, 2016). Duggan (2015) identified that of Facebook's total number of users, 70% visit the platform daily, while for Twitter this is 38%. Thus, more people might have a chance of being engaged in emergency information via Facebook rather than Twitter. Further investigations, using survey and interview, would identify their motivations and reasons for their engagements.

There was a limitation on data collection. Since we collected data from a Facebook fanpage of the city of Baton Rouge, we were not able to explore how the shared information on a user's Facebook page will be re-shared with other social networks, compared to a *retweet* on Twitter. This would enable us to precisely measure information diffusion across the community structure of social media. Also, the network is limited to Facebook, so it does not include other online and offline networks created during disaster responses.

It is critical for the public to receive accurate, reliable and timely information from emergency agencies during disasters. Many literatures identified that social media 1) influences social consciousness, 2) leads rapid information delivery, and 3) reach a broader and more targeted population than any conventional methods(Mohammadi et al., 2016). Thus, social media such as Twitter and Facebook is expected as a powerful tool for rapid information diffusion in emergency.

As our findings reveal, SNA could be applied to understand characteristics of online social network and structure in depth including critical central and intermediate vertices in the network. The results can be used to understand heterogeneity in social networks and applied to accelerate information diffusion in emergency. Thus, emergency agencies need to equip a network analysis tool and database to analyze local-, state- and national level social network in emergency. Also, a collaboration with social media such as Facebook and Twitter will be beneficial to improve reliability of data collection, monitor real-time data, and expedite the overall SNA process in emergency.

As discussed in Section 7, organizations with high betweenness centrality play a critical role to connect online communities in a social network. Thus, emergency agencies have an online partnership with public and private sector including NGOs and NPOs to create stronger bonds in their social network.

A future study is needed for understanding characteristics and effectiveness of different social media platform including Twitter, Facebook, Google+, YouTube and Instagram in disaster responses such as their feasibility and reliability as an information diffuser in emergency. Most questions could be answered by a multi-case study approach that would compare the use and effectiveness of social media across a broad range of disasters. Another future study is also needed for isolated vertices where information might not be reached via an existing online network. Therefore, application of search and location-based advertising services for emergency information is a crucial research topic to improve online information diffusion performance.

Acknowledgement

We are thankful to Dr. Natalie Lambert at the Brian Lamb School of Communication at Purdue University for her invaluable guidance and encouragement during this data collection and analysis.

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