INTEGRATED FLOOD AND SOCIO-ENVIRONMENTAL RISK ANALYSIS FOR PRIORITIZING ABC ACTIVITIES

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1. Background and Introduction

The need to accelerated bridge construction (ABC) activities due to flooding (e.g., accelerated bridge upgrade prior to flood events and accelerated bridge repair after flood events) has complex interdependencies with many physical, social, and environmental factors in urban areas. The interdependencies get exacerbated in coastal areas, such as southeast Florida, because of the pronounced effects of climate change such as extreme storm events and sea level rise (SLR) impacts on surface and ground waters. According to the National Oceanic and Atmospheric Administration (NOAA) reports, 612% increase in flooding in the United States has been reported from 1960s (NOAA 2015). Flood-related factors can contribute to bridge scour, the biggest cause of bridge failure in the United States (52% of all failure cases) (Cook et al. 2015). Besides, depending on bridge location, rainfall patterns are highly functional in hydraulic failure of bridges Kandel et al. 2019).

Because of the limited available budget for accelerated upgrade/repair processes, a comprehensive decision support tool is needed to prioritize bridges in terms of the vulnerability of bridge location and risk level of each bridge to support Department of Transportation (DOT) decision makers in project selection. To refine funds allocation for the ABC there is a need for a simplified, yet accurate, methodology to estimate bridge vulnerability to several interdisciplinary factors. The methodology should practice existing data and display important variables to assess the vulnerability of urban areas and risk of bridges against urban flooding considering various flood-related and socio-environmental factors. Considering factors such as extreme storm events, storm surges, and SLR mostly in coastal areas, flooding is not only the natural hazard with the distinguished impact on bridge failures and the amount of damage and costs resulting from that, but it is difficult to model and accordingly plan for as well. Furthermore, given population growth rates, urbanization, and poor land use practices in flood-prone areas, flood risk has increased significantly recently. Floods and associated hazards will become more persistent, extreme, and regular along with climate change and socio-environmental effects, notably in already vulnerable areas. The project first performs a vulnerability/risk assessment considering urban flooding and bridge scouring, social, and environmental factors, and then develops a multi-criterion, multi-stakeholder decision analysis framework in geographic information systems (GIS) environment to assign a risk factor to each bridge in the study area. The framework is applicable as a decision support tool for selecting accelerated bridge upgrade or accelerated bridge repair projects by decision makers. As a case study, the developed framework will be used for a risk-based prioritization of existing bridges in Miami-Dade County with the purpose of selecting projects for accelerated bridge upgrade or repair.

2. Problem Statement

The success of ABC projects depends on several factors which result in improving safety, reducing traffic load, costs, and yielding better overall travelling experience (Wang et al., 2011). Decision-makers need to assure that the ABC techniques are thoughtfully viewed since many of the projects will have only access to the limited budgets and time (Chaphalkar et al., 2013).

Feasible candidates for ABC may be suspended or cancelled due to safety hazards, standardization, inexperienced contractors and manufacturers, technical problems related to bridge strength and long-term performance, as well as the lack of funding. Therefore, the decision-making process considers one basic stage as an early involvement in ABC projects to propose a decision support tool for prioritizing ABC activities in the presence of limited budgets before the construction process.

ABC projects in urban areas interacted with traffic potentially have complex interdependencies with several natural hazard, (e.g., flood), environmental, and social factors (Jia et al., 2018). Past studies have asserted that flood has been the most common natural disaster, accounting for 43% of all disasters between 1995-2015 in the world (CRED, 2015). A study by Wardhana and Hadipriono (2003) found that 53% of bridge failures in the United States between 1989 to 2000 were because of scour due to floods. In point of fact, the rapid water flow generated by flood often gives rise to accumulated debris, which yields a compounded loading impact on bridges and may cause structural damage or failure (Kalantari et al., 2017). Meanwhile, the structural integrity of a bridge may be degraded by the corrosion of steel reinforcements. In this case the failure risk of bridges under flood hazards magnifies and their failure can become more sever (AASHTO, 2008). Therefore, reducing the construction time through ABC methods can potentially minimize the risk of flooding due to temporary flood diversions during the construction phase. High temperatures as an environmental risk factor, also can cause health issues for human, impacting ABC progress, and affect flooding conditions due to the effects on soil hydraulic properties and evapotranspiration processes. Social and demographic factors in adjacent areas of bridges (e.g., population, residents' age, race, and income, and age of the buildings) have implications in the need to an ABC process and can impact the construction speed. For example, ABC can help faster revitalization of a high crime rate neighborhood based on urban master plans while ABC activities may also be negatively impacted in those neighborhoods.

To obtain more realistic and accurate vulnerability assessment of bridge failure against floods, the flood-related factors and interdependence factors should be included in the risk analysis (Arneson et al., 2012). Complexity, multidimensionality, and inherent uncertainties of urban systems require the risk analysis to be comprehensive and able to address different criteria, multiple stakeholders, and spatial aspects of the problem (Glas et al., 2019). The proposed study addresses the need to a comprehensive risk-based multi-criteria multi-stakeholder decision analysis framework that can be used as a decision support tool for prioritizing ABC activities in the presence of limited budgets. Developing the multi-criteria multi-stakeholder decision analysis framework option will consider, among other things, early contractor involvement in order to ensure the project can be constructed in the construction site considering the time and budget allotted. The proposed project once would be focused on the vulnerability assessment of bridge failure against floods and will also be geared towards addressing socio-environmental factors.

3. Objectives and Research Approach

The objective of this study is to develop a multi-criterion, multi-stakeholder decision analysis framework in GIS environment to assess the vulnerability of urban areas and risk of bridges against flooding and socio-environmental factors. The framework can be used as a decision support tool for selecting accelerated bridge upgrade or accelerated bridge repair projects by decision makers. As a case study, the developed framework will be used for a risk-based prioritization of existing bridges in Miami-Dade County with the purpose of selecting projects for accelerated bridge upgrade or repair. The overall approach is to introduce GIS and multi-criteria decision analysis (MCDA) to assess the vulnerability of urban areas and risk of bridges against flooding and socio-environmental factors. The project also describes the use of GIS during the case study for different tasks including, but not limited to the collection and pre-processing of physical, social, and environmental data. Figure 1 presents the flowchart of the proposed methodology. This study considers three types of vulnerability: physical, social, and environmental vulnerability. Definition and details of each group are discussed in Task 2.

Once the GIS data discussed in Task 2 are collected, two major steps of the proposed methodology are as follows:

1. Creating vulnerability maps:

By using the collected physical, social, and environmental GIS data, the developed framework will identify vulnerable urban areas against flooding and socio-environmental factors and creates vulnerability maps. A vulnerability map is first created for each major criterion (i.e., physical, social, and environmental vulnerability maps). Then, the vulnerability maps will be combined using the developed MCDA framework. The output of this step would be an integrated vulnerability map against flood and socio-environmental factors. The framework is capable of handling problems with multiple stakeholders or decision makers. Therefore, the opinions of decision makers about the relative importance of physical, social, and environmental factors can be incorporated into the framework through a group decision making process.

2. Creating risk maps:

The vulnerability map will be combined with existing data about history of flooding, traffic loads and structural conditions of the bridges to generate risk maps that provide risk levels for each of the existing bridges in the study area. Example of bridge related data include type, number, and configuration of piers, scour countermeasures such as rip raps, collars, and sacrificial piles, age of bridges, and structural conditions based on inspections to assess scour potential. High risk bridges can be selected by decision makers (e.g., state DOTs) for accelerated upgrade (retrofit) prior to flood events or accelerated repair after flood events.

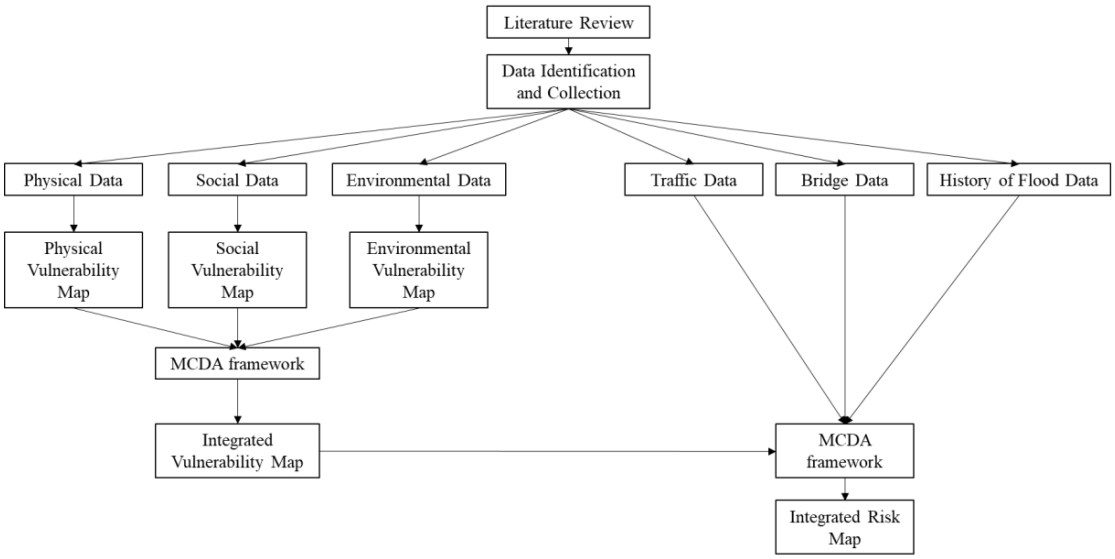


Figure 1. Flowchart of the proposed methodology. Comprehensive vulnerability map for the study area and comprehensive risk map indicating a risk level for each bridge are two final products of the study.

4. Description of Research Project Tasks

Task 1 – Literature Review

The objective of literature review is to identify existing state of the knowledge and practice about socio-techno-environmental risk analysis approaches for natural hazard problems in urban areas. Also, another literature review is performed to identify the existing studies on the interdependencies of climate factors, land factors, bridge characteristics, and bridge scour to be leveraged in the study.

Urban infrastructures, namely bridges, as the result of urbanization, are increasing in demand. However, due to natural hazards and climate change effects, such as floods, SLR in coastal areas, high temperature, and severe storms, construction might be in the risk of failure. According to the United Nations Office of Disaster Risk Reduction (UNDRR) risk is the combination of the probability of a hazardous happening and its negative consequences which develop out of interactions between natural or man-made hazard(s), vulnerability, exposure, and capacity (Birkmann et al., 2010). Vulnerability can be the combination of multi criteria categories, including physical, social, economic, environmental, psychological, structural, and institutional (Pescaroli and Alexander, 2019; Ghajari et al., 2017). The Intergovernmental Panel on Climate Change (IPCC) considered the risk concept, as a function of hazard, exposure, and vulnerability, instead of the vulnerability definition (IPCC 2012b). This concept determines that the damaging effects of a hazard depend on the local vulnerability of an exposed society. Considering the vulnerability as one element of the hazard risk, it has a multidimensional nature which is varying across temporal and spatial scales. It is required to decrease the vulnerability before and after the hazard's occurrence in the context of coping and adaptation. While coping is referred to ex post actions, adaptation is normally associated with ex ante actions (IPCC 2014) that boost resilience (Golz, Schinke, and Naumann 2014), yet in many applications, vulnerability still is considered only as the impacts of a hazard (Yang et al. 2018; Weis et al. 2016; Kc, Shepherd, and Gaither

2015). In recent years, a better representation of hazard and vulnerability along with spatial science (e.g., GIS) has been challenging. Recent studies used 'integrated' (Weis et al. 2016), 'hybrid' (Roodposhti et al. 2016), 'MCDA' and 'system-thinking' terms (Gomez Martin et al. 2020). However, most definitions are not fitting to different areas of hazards because of geographical differences, human interactions, and inadequate data (Robinson et al. 2019), governance ordering (Driessen et al. 2018), the involvement of stakeholders and dynamism of cities (Ciullo et al. 2017). The vulnerability also varies over different time periods and due to different causes, which provide challenges for the assessment in different areas (Pescaroli and Alexander 2019). Yet, bridge failures are highly interdisciplinary, a mixture of various factors that might not result in a significant bridge failure if they occur individually. For instance, in coastal areas, such as southeast Florida, the pronounced effects of climate change such as extreme storm events and SLR impacts on surface and ground waters may cause bridges failure if they happen along with high traffic loads. Regarding the multidisciplinary nature of risk assessment, MCDA have been considered as a popular, common, and real-world-based challenge way focusing on the risk assessment problems.

For massive computational efforts on data collection and analysis, GIS technology including various spatial and temporal dimensions has been commonly applied to multi-dimensional problems (Abuzied et al., 2016; Pradhan et al., 2014; Razavi Termeh et al., 2018; Santos et al., 2017; Weerasinghe et al., 2018). Integrated analysis is feasible using GIS in both technical and socioeconomic features (Chen et al., 2015b; Gigovi et al., 2017; Santos et al., 2017). A geographic information system (GIS) can integrate and analyze data from various sources and report the results, which makes it a valuable tool in the management process (Eastman et al. 1997). GIS is applicable for damage assessment due to its ability to combine results from the hydraulic model and socio-environmental information. Complex decision-making situation like flood risk assessment that consists of several spatial criteria can be developed through Geographic Information Systems' capability of visualization, analysis, and management of spatial data (Meyer et al., 2009, Papaioannou et al., 2015, Tang et al., 2018). GIS is an important tool in analyzing and assessing the effects of natural hazards (Haq et al., 2012, Kanani-Sadat et al., 2014, Karimipour and Kanani-Sadat, 2016, Pourghasemi et al., 2013); therefore many studies have investigated flood analysis and developing flood risk assessment map using the capabilities of GIS (Sanyal and Lu, 2009, Strobl et al., 2012, Tehrany et al., 2014a, Tehrany et al., 2014b, Termeh et al., 2018, White et al., 2010, and Khosravi et al. 2018). Considering mapping approaches, the discussion of selecting an appropriate indicator is a challenge (Malczewski and Rinner 2015). Indicator's assignment and the quality of available data require a deep conception of the complex system. Another challenge is the criteria weights allotment as the complexity of systems is limiting the criteria to have equal influence in a hazard (Jung et al., 2011). For vulnerability and exposure mapping assessments, studies mostly assess equal weighting (Hazarika et al. 2018) or either subjective or objective (Birgani and Yazdandoost 2018) methods for weights calculation. Furthermore, data collection/preparation is the most important step and can be the most time-consuming part of an analysis. Generally, study of natural hazards requires multiple datasets to distinguish the spatial changes and the processes of hazards (Martinez and Le Toan 2007). Natural hazards could be under the effects of several factors, namely geomorphology, vegetation, geologic and hydrologic parameters, and patterns that must be considered in providing of the flood risk assessment maps. Therefore, risk assessment mapping is a MCDA process (Hwang and Lin, 2012, Malczewski, 2006). Multi-criteria decision analysis (MCDA) has been recognized as an essential tool for analyzing complex decision problems that often concern for incomparable data or criteria

(Hwang and Yoon 1981; Malczewski 2006). Analytical Hierarchy Process (AHP) is a well-liked method of MCDA (Pourghasemi et al. 2012), based on experts' knowledge in assignment groups and weighted grading. Fernandez and Lutz (2010) have estimated the efficiency of MCDA and GIS for mapping any area adjacent to a river, lagoon, or lake likely to have floods anytime the water level rises in Tucuman Province, Argentina. According to this study, the AHP method in the GIS environment is effective in generating natural disaster hazard maps with reasonable accuracy. Zou et al. (2013) described the AHP technique as a cost-effective with a clear understanding and effective analysis method for flood hazard evaluation. Subramanian and Ramanathan (2012) applied the AHP technique in urban and regional research. To evaluate natural disaster risks there are other methods of MCDA, namely Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Multi Attributive Border Approximation Area Comparison (MABAC). TOPSIS has been indeed used in flood hazard management due to its ability to cope with multiple attributes (Brito and Evers 2016). Mojtahedi and Oo (2016) presented an integrated non-parameter resampling bootstrap technique and TOPSIS to assess the flood risk of Australia's states. Zhu et al. (2018) extended a TOPSIS-based model for Reservoir flood control operation (RFCO) problem. Luu et al. (2019) developed the brand-new multiple linear regression TOPSIS for Vietnam's evaluation flood risk. Several studies also have used the fuzzy-TOPSIS technique (Jung et al. 2011; Lee et al. 2014; Shariat et al. 2019). In general, MCDA methods are approaches that have been most popular in flood hazard assessment applied by many researchers in recent studies (Rahmati et al. 2016; Rahman et al. 2019; Ogato et al. 2020). Improving the accuracy of these models has always been one of the main concerns of researchers and decision makers. While the existing literature provides no universal guideline in finding the best model in a region due to the models' limitations, some studies (e.g., Shafapour Tehrany et al. 2019; Hong et al. 2018; Costache et al. 2020; Rahman et al. 2019) showed that combining several methods may lead to higher accuracy in flood susceptibility assessment. Table 1 lists some of the GIS-based, MCDA, and combined GIS-MCDA studies regarding the flood risk assessment in urban areas.

Ozturk and Batuk (2011) applied AHP to identify the flood vulnerability, and then, use GIS to generate the flood risk map. Zou et al. (2013) consider AHP as one of the most intellectual, affordable, and decisive methods for flood risk assessment. Some studies have been assessing flood risk integrated with socio-economic and environmental factors. Cutter et al. (2013) presented a methodology to assess flood risk along with social vulnerability in USA. Escuder-Bueno et al. (2012) and Ballesteros-Canovas et al. (2013) applied integrated flood risk assessment in Europe. Gain et al. (2011 and 2013) indicated that seasonal rainfall, upstream flow, and sea-level rise increase the flood risk in flood-prone countries. Gain et al. (2012); Gain and Schwab (2012); Dewan (2013) and Rouillard et al. (2014) introduced the random economic changes, population growth, urbanization, poor policies, and land-use changes as the flood risk assessment factors. Bubeck et al. (2012) related the anthropogenic activities such as land-use changes to flooding risk. Nicholls et al. (1999) asserted that coastal as well as low-laying areas are more prone to the flood risk because of climate change effects and population migration. Khosravani et al. (2016) considered geo-morphological and geo-environmental factors as the effective factors on the flood risk. Furthermore, GIS-based MCDA can apply combining process to spatial data and information layers for the decision-making process (Malczewski, 1999, Malczewski, 2006). Arabsheibani et al. (2016); Boroushaki and Malczewski (2010); Chen et al. (2011); Shariat et al., 2019, combined GIS and MCDA to come up with a powerful spatial decision support system.

Table 1. Examples of GIS-based, MCDA and combined GIS-MCDA studies for flood risk assessment in urban areas

	Authors	Indicator			
		Social	***Physical***	***Environmental***	***Method***
Reference	Ullah & Zhang, 2020	Land use	DEM, slope, drainage density	NDVI, rainfall intensity	GIS
	Cai et al., 2019	Land use, building density, population density	DEM, slope, impermeability	Water (flood) depth, flood duration	GIS
	Kabenge et al., 2017	Land use	Slope, drainage network, distance from drainage channel	Rainfall intensity, flow accumulation	GIS
	Dewan et al., 2007		DEM	Flood depth, flood frequency	GIS
	Hadipour et al., 2020	Population density, population with any sort of disability, people age & gender, education level		Tidal range, wind speed, storm surge, SLR	MCDA
	Gain et al., 2015	Land use, building age, type & material, population density, traffic load, income, education level	DEM, river network	Flood frequency, rainfall intensity	MCDA
	Cutter et al., 2013	Land use, population density, income, education level		Flow velocity, water depth, flood frequency	MCDA
	Ballesteros et al., 2013		DEM	Flood frequency, flood depth, water velocity	MCDA
	Meyer et al., 2009	Annual average damage, areas with accumulation potential of pollutants, average affected population, hotspots (hospitals, schools, daycare)	Erosion potential		MCDA
	Toosi et al., 2019	Land use	DEM, drainage density, soil type	rainfall intensity, flood frequency	MCDA-GIS
	Rincon et al., 2018	Land use, people age, family structure, income, education level, population density,	Slope, distance from drainage channel	rainfall intensity, flood frequency	MCDA-GIS
	Fernandez & Lutz, 2010	Land use	DEM, slope, distance to the drainage channels, depth to groundwater table, impermeability		GIS-MCDA
	Vignesh et al., 2021	Population density, hotspots (hospitals, schools, daycare)	DEM, slope, river network, distance from drainage channel	NDVI, rainfall intensity, flood frequency	GIS-MCDA

Different metrics or indicators have been used by researchers in flood risk analysis studies. Singh et al., 2020, consider six different factors that have significant impact on flooding in India. The introduced factors are rainfall intensity, curve number, time of travel, surface slope, Manning's coefficient, and drainage density. Kia et al., 2012, introduce rainfall, slope, and flow as the effective natural hazard factors in urban sectors. Zou, et al., 2012; Quan, 2012, and Gao, 2016, apply population disaster and housing loss effective in assessing flood-prone region disaster risk. Zhang et al., 2008, focus on the relation of temperature fluctuation with flood disasters in the context of climate change. Ruiling et al.,2020, select five primary and nineteen secondary flood risk assessment indicators, including annual precipitation, frequency of rainstorm, vegetation coverage, drainage density, urbanization rate, population density, building density and economic density. They consider two vulnerability indicators including the old and young population per unit area and the proportion of crops per area; two secondary indicators including economic and crop loss were considered as the disaster loss criterion. Gain et al., 2015 indicate the flood risk is the result of extreme hydrological events in addition to physical and social indicators. They introduce building age and types, building materials, land-use map, number of cars and population density as the vulnerability indicators. Wang et al., 2020 address fourteen flood risk assessment indicators including physical geography and socio-economic ones, out of which there are seven hazard indicators and seven vulnerability indicators. Digital elevation model (DEM), soil texture, rainfall intensity, the normalized difference vegetation index (NDVI), rainstorm frequency, drainage density, and slope data were defined as the hazard indicators by Wang et al. (2020) while they used gross domestic product, road network density, average schooling years, population density, grain output, and per capita disposable income as the vulnerability indicators. Glas et al., 2019, develop flood risks maps integrated with social, economic, and physical vulnerability maps for the catchments of the river Moustiques, Haiti, a data poor region. They use rainfall depth, DEM, soil texture, land-use/cover, and channel characteristics in the hydrological model. Only material damages to buildings and roads considered as the physical vulnerability, whereas economic vulnerability also consider the economic damages to farmlands.

Karatzetzou et al., 2021, present homogenizing methodology to combine the single flood risk indicators and derive a combined flood risk assessment scenario for roadways, bridges, and tunnels in Greece. Andrić et al., 2016, classify the potential hazards based on the collapse reason into six groups, including windstorm, hydraulic, traffic, construction, and human-made hazards. They introduce fifteen risk indicators contributed to bridge failure, including earthquakes, tsunamis, hurricanes, floods, debris, scour, ice, soil, the age of the bridge, collision, overloading, deterioration, construction and design, fire, and terrorist attack. Kattell and Eriksson, 1998, indicate that flowing water cause scouring effect around the bridge piles and foundation, which remove the material and lead to the bridge failure. They also consider the scour as the most important factor in highway bridge failure in the United States. Yang et al., 2020, bring in a risk-oriented method to evaluate the vulnerability of coastal bridges under climate change and socio-economic changes. In this research, five factors are under consideration including temperature fluctuation, SLR, hurricane frequency, storm surge, aggregated appreciation, population growth and asset appreciation. Barankin et al., 2020, use Federal Emergency Management Agency (FEMA) to determine the critical elevation cutoffs, annual average daily traffic, evacuation routes, and bridge height over water ways as indicators for analyzing the vulnerability of transportation assets to socio-economic and flooding events on costal Massachusetts regions. Mondoro et al., 2016, propose an optimal risk-based method for costal region bridges, which address natural hazards including hurricanes and the updated flood maps along the coastal regions performed by FEMA as well as economic and social indicators including length of the detour, duration of the detour, average daily traffic, average vehicle occupancy, and average detour speed.

In the context of socio-economic vulnerability in risk analysis of highway bridges, literatures have been using various combinations of factors. Tobin and Montz, 1997 introduce age, gender, race, and income as the vulnerability indicators. Schmidt-Thome, 2005 present land management/development and disaster mitigation plans as the social vulnerability factors. Table 2 lists some of the bridge failure risk assessment indicators due to socio-economic, environmental, and physical factors.

Table 2. Social factors affecting risk assessment of bridges

		Indicator								
		land use	population density	people age	people gender	education level	income level	building type	building density	employment rate
Reference	Tobin & Montz, 1997			*	*		*			
	Turner et al., 2003	*	*							
	Chen et al., 2003		*				*	*		
	GTZ, 2004		*			*				
	UNDP, 2004		*							
	UN/ISDR, 2004					*	*			
	Allen & Thanassoulis, 2004		*				*			
	Cardona et al., 2005		*				*	*		*
	Messener & Meyer, 2005		*	*	*					
	Rygel et al., 2006			*						
	Lee et al., 2009				*		*			
	Meyer et al., 2009		*							
	Cheng-Hsien et al., 2011			*			*		*	*
	Zou et al., 2012	*	*							
	Quan, 2012	*								
	Yamin et al., 2013		*							
	Te Linde et al., 2011	*								
	Dewan, 2013	*								
	Ouma & Tateishi, 2014	*								
	Gain et al., 2015		*							
	Ronco et al., 2015		*							
	Mondoro et al. 2016		*							
	Lee, G. et al., 2017		*							
	Rincon et al., 2018	*		*						
	Glas et al., 2019	*								
	Hadipour, V et al. 2020		*	*	*					*
	Singh et al., 2020	*								
	Yang et al., 2020		*							
	Barankin et al., 2020		*							
	Ruiling et al., 2020	*	*							*
	Wang et al., 2020		*							

Table 3. Environmental and physical factors affecting risk assessment of bridges

		Indicator										
		NDVI index	air quality	rainfall intensity	flood depth	flood frequency	flood duration	flow accumulation	wind speed	SLR	flow velocity	water quality
Reference	Turner et al., 2003		*									
	Chen et al., 2003		*	*								
	GTZ, 2004											*
	UN/ISDR, 2004		*									*
	Allen & Thanassoulis, 2004				*	*	*				*	
	Dewan et al., 2007				*	*						
	Meyer et al., 2009			*				*				
	Cheng-Hsien et al., 2011			*								
	Kia et al., 2012			*								
	Zou et al., 2012			*								
	Quan, 2012				*	*	*					
	Bloetscher et al.,				*					*		
	Cutter et al., 2013				*	*					*	
	Ballesteros-Ca´novas et al., 2013				*	*					*	
	Yamin et al., 2013					*			*			
	Te Linde et al., 2011			*								
	Zou et al., 2012			*								
	Dewan, 2013			*								
	A.Johnston et al., 2014								*	*		
	Ouma & Tateishi, 2014			*								
	Gain et al., 2015			*				*				
	Ronco et al., 2015										*	*
	Andric et al., 2016					*			*			
	Terti et al., 2017				*	*	*	*				
	Kabenge et al., 2017			*				*				
	Lee, G. et al., 2017			*								
	Rincon et al., 2018			*		*						
	Cai et al., 2019				*		*					
	Toosi et al., 2019			*		*						

		Indicator										
		NDVI index	air quality	rainfall intensity	flood depth	flood frequency	flood duration	flow accumulation	wind speed	SLR	flow velocity	water quality
Reference	Glas et al., 2019			*		*						
	Vignesh et al. 2020	*		*		*						
	Hadipour et al. 2020								*	*		
	Singh et al., 2020			*								
	Yang et al., 2020		*						*			
	Barankin et al., 2020			*		*						
	Ruiling et al., 2020			*								
	Ullah and Zhang, 2020	*		*								
	Wang et al., 2020			*		*						
	Karatzetzoi et al., 2021			*		*						

Table 4. Physical factors affecting risk assessment of bridges

		Indicator										
		DEM	slope	road network	bridge network	land cover	imperviousness	canal network	soil type	soil permeability	distance from drainage channel	river network
Reference	Kattell & Eriksson, 1998	*			*				*			
	Turner et al., 2003		*							*		
	Chen et al., 2003	*				*						
	GTZ, 2004								*			
	UN/ISDR, 2004								*			
	Dewan et al., 2007	*										
	Lee et al., 2009			*		*						
	Meyer et al., 2009								*			
	Fernandez & Lutz, 2010	*	*							*	*	
	Te Linde et al., 2011	*	*			*					*	*
	Cheng-Hsien et al., 2011		*									
	Bloetscher et al.,			*	*	*					*	*
	Kia et al., 2012		*									
	Zou et al., 2012	*	*			*					*	*
	Yamin et al., 2013			*					*			
	Ballesteros-Ca´ et al., 2013	*										
	Dewan, 2013										*	
	Johnston et al., 2014	*		*	*							
	Gain et al., 2015	*		*								*
	Ronco et al., 2015			*								
	Andric et al., 2016	*			*				*			
	Mondoro et al. 2016	*			*							
	Terti et al., 2017	*	*								*	
	Lee et al., 2017		*								*	
	Kabenge et al., 2017		*					*			*	
	Rincon et al., 2018		*								*	
	Toosi et al., 2019	*	*					*	*		*	

Task 2 – Data Identification, Collection, and Analysis

Study Area

Miami-Dade County, in southeast Florida (Figure 2), one of the low-lying areas on the southeast coast of the United States exposed to the risk of flood and storm surge (Chen et al. 2015; Woetzel et al., 2020), is used as the case study. To respond to the natural hazards, the characteristics of social groups are always important in terms of influencing the society's limitations and capacities. In fact, the more indicators within study we use, the more realistic would be the explained model. However, it is fundamental to remove co-linear and the same aligned objects in the dataset which reduces indicators. As risk analysis level, an interaction of multi hazardous factors and the combination of environmental and human elements exposed to the risk is important to get a realistic result. Therefore, these terms are considered by applying a specific combination of socioeconomic and environmental conditions present at the Miami-Dade County level. Miami is the ninth in population exposure to climate extremes among world port cities and has the population of 2,721,110 with a growth rate of % 0.08 in the past year (World Population Review) and has the largest amount of exposed assets and the population vulnerable to sea-level rise in the world. For instance, drivers' age that causes different social vulnerability is diverse within the county and neighborhoods. Again, risk vulnerability varies by overall occupancy households. Miami-Dade's estimated beachfront property value is more than $14.7 billion, not including infrastructure. King tides, flood events with high tide conditions, have been causing serious damages to the constructions including bridges and transportation systems. These damages due to the coastal flooding will become even worse with the rising sea.

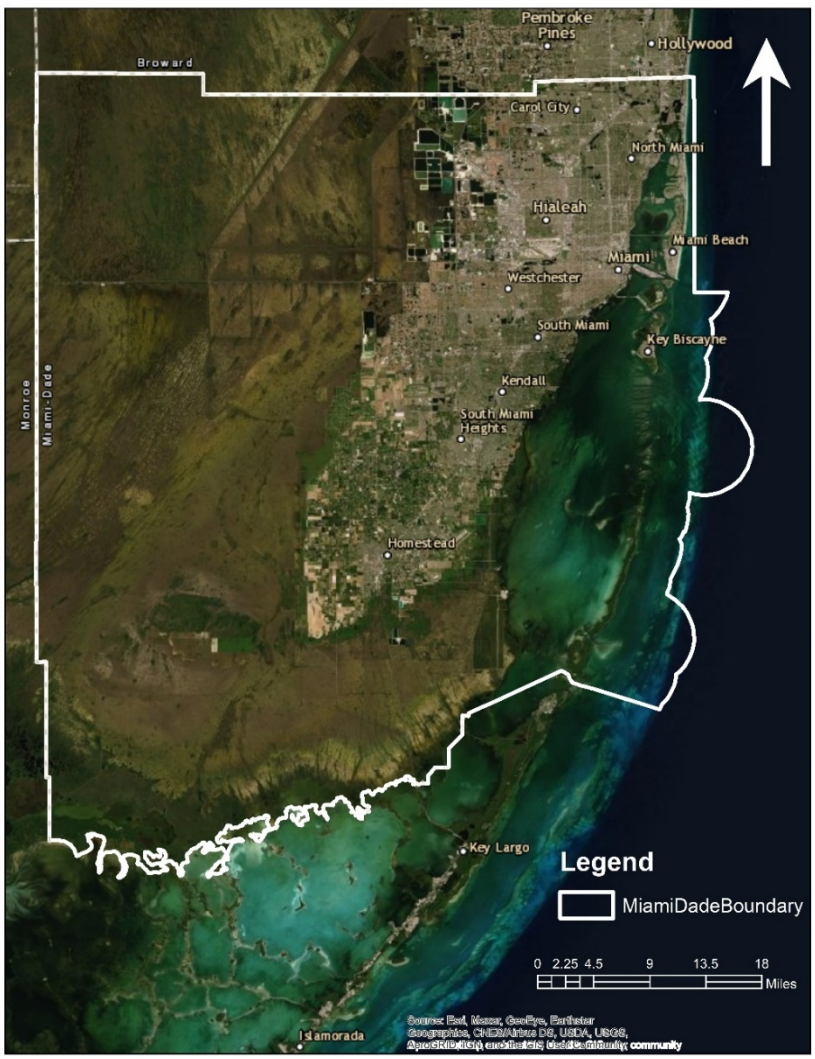


Figure 2. Miami-Dade County Boundary

Determining Suitable subdivisions in the study area

In the MCDA method, the aim is selection of well-determined and favorable locations in the study area where the defined indicators can be established. In this study, to take the criteria into account, choosing the most suitable subregions in Miami-Dade County is required. Non-urban areas or area of vegetation are not considered in the risk assessment process. Therefore, the main idea in this section is to eliminate those areas of the map to form the initial layer of the base map. The subdivision is used for regions and sites when a large area of land is to be observed as smaller individual parcels. In this study, we consider two different subdivision strategies: a subdivision based on zip code, Figure 3, and a subdivision based on subwatersheds, Figure 4. Biscayne Bay watershed (2500 km^2) is located along the southeastern coastline of Florida, Miami-Dade County, which includes the city of Miami. Its western boundary lies close to the Florida National Park and green spaces. Figure 4 presents subwatersheds in the study area from the South Florida Water Management District models.

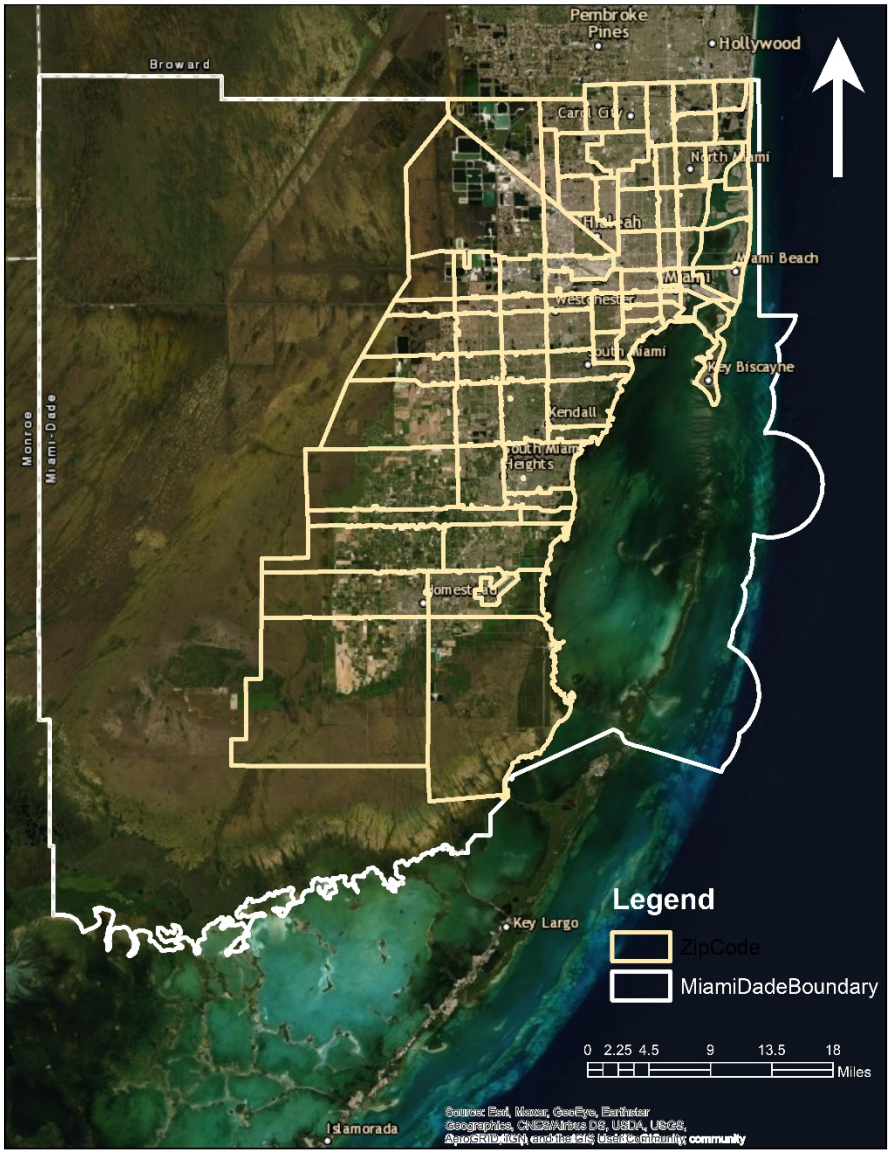


Figure 3. Miami-Dade County Zip Code Boundary

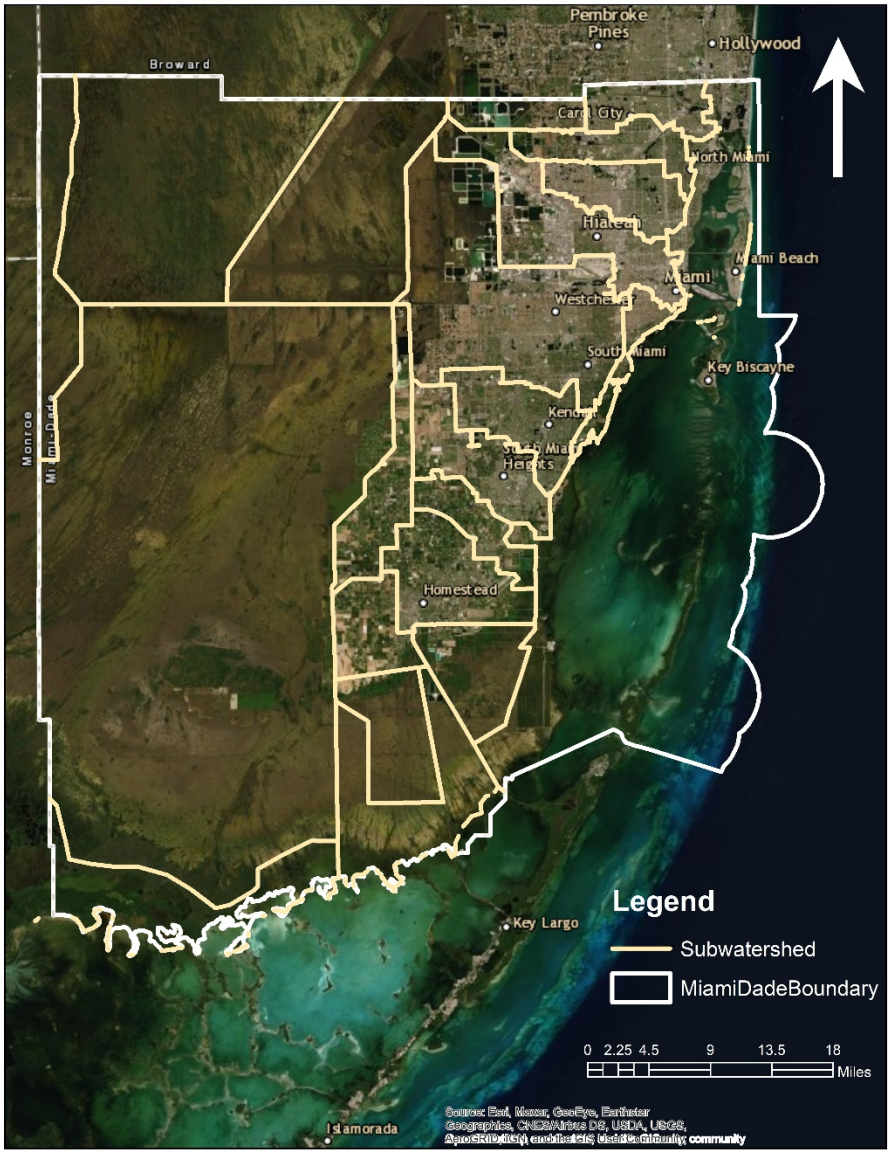


Figure 4. Miami-Dade County Subwatersheds Boundary

The geographic information system (GIS) is a system which uses data referenced by spatial coordinates. Observation and collection of data as well as storage and analysis to the use of the information derived are crucial part of a decision-making process. No solid guideline concerning which data to choose and how to analyze is existing in the literature. In terms of social factors, social and cultural heterogeneity changes in different urban communities and then, many various methodologies can be applied to assess social vulnerability at each scale and system. This process of identifying data consists of several processes, including acquiring satellite or aerial photographs, maps, collecting demographic information or data on rainfall-runoff, and conducting field surveys. To be strategic, data sets used in this study include integrated data collected from different sources. We are not arguing the different data selections other researchers have introduced so far, yet there, we developed a new data selection path which well aligned to the present research's goals. Many researchers combined rainfall intensity with population density for risk analysis. Some other studies added more social indicators to their methodology, however, there is still limited number of studies that explored the integration of temperature, NDVI, traffic load, road accessibility with flood risk factors namely rainfall intensity. Therefore, based on the performed literature review (looking at the data used by other researchers in similar studies) and specific conditions of the current

research and study area, we ended up with using the data in Table 5 to 7. We consider three types of data: physical, social, and environmental vulnerability data.

The multidimensional nature of risk analysis makes the framework overlapping. Then, a comprehensive data collection is organized under three headings, environmental, social, and physical categories; each one has its subcategories, which map out the major elements of interest. Every category introduced in this study includes factors causing impacts in the context of prioritizing ABC activities which are strongly coupled, complex, and evolving. There are many examples of data collection that make bridge construction vulnerable to extreme events, however, limited number of them have the potential to provide risk and as mentioned some of them have been overlapped. This understanding of data collection can result in positive impact on the accuracy of final risk maps. For example, in some data collection development strategies land cover, soil permeability, soil texture and imperviousness have been defined in the literature, but this research attempts to frame an approach to omit/combine data often have overlapped to provide meaningful and specific assessments rather than introducing new data. Besides, individual data in a group, for example NO2, CO2, PM2.5 and PM10 in the context of air quality, is analyzed to find the most meaningful data with a good diversity in the study area. Based on the research, a rapid reduction in most of the pollutant concentrations (PM10, PM2.5, CO, SO2), and an increment in ozone concentration was observed due to the lockdown because of Covid-19 and then in result shutting down of power plants, transportation, and other industries. Therefore, in this study air quality index related to NO2 is selected as an input which shows meaningful distribution over the study area than the other ones. According to EPA, air quality index ranges from 0 to 500, which provides indicator of the quality of the air and health category.

Table 5. Environmental data and indicators

	Data	Indicator	Vulnerability	Source
Environmental	Air quality index	0-50	VL	EPA
		50-100	L	
		100-150	M	
		150-200	H	
		>200	VH	
	Temperature (°C)	<26	VL	weather.gov
		26-28	L	
		28-31	M	
		31-33	H	
		>33	VH	

Table 6. Physical data and indicators

	Data	Indicator	Vulnerability	Source
Physical	Imperviousness (%)	<1	VL	NLCD
		1-20	L	
		20-50	M	
		50-80	H	
		>80	VH	
	Land cover	water bodies	VL	NLCD
		green spaces	L	
		low developed	M	
		medium developed	H	
		high developed	VH	
	Hydrologic soil group	A	VL	USGS
		B	L	
		C, B/D	M	
		C/D	H	
		D	VH	
	Depth to water table (m)	>12	VL	USGS
		9-12	L	
		5-9	M	
		2-5	H	
		<2	VH	
	Slope (%)	1-2	VL	DEM
		2-5	L	
		5-8	M	
		8-16	H	
		16-30	VH	
	Distance from canal (m)	0-30	VL	GIS distance analysis
		30-45	L	
		45-70	M	
		70-130	H	
		>130	VH	
	Hurricane evacuation zones	E	VL	FL Division of Emergency Management
		D	L	
		C	M	
		B	H	
		A	VH	
	Annual rainfall (in)	54-56	VL	NOAA
		56-58	L	
		58-60	M	
		60-62	H	
		62-64	VH	

Table 7. Social data and indicators

	Data	Indicator	Vulnerability	Source
Social	per capita income ($)	>60,000	VL	miamidadematters.org
		40,000-60,000	L	
		30,000-40,000	M	
		20,000-30,000	H	
		10,000-20,000	VH	
	Population density (ppl/sq mile)	<10,000	VL	
		10,000-25,000	L	
		25,000-35,000	M	
		35,000-45,000	H	
		>45,000	VH	
	age 65+ population density (ppl/sq mile)	<100	VL	
		100-300	L	
		300-500	M	
		500-700	H	
		>700	VH	
	Crime index	<100	VL	crimegrade.org
		100-150	L	
		150-200	M	
		200-250	H	
		>250	VH	
	Average Commute time (min)	<25	VL	miamidadematters.org
		25-30	L	
		30-35	M	
		35-40	H	
		>40	VH	
	land-use	Vacant/Institutional	VL	opendata.arcgis.com
		Low density residential/ Industrial	L	
		Medium density residential	M	
		Commercial/High density residential	H	
		Health	VH	

In what follows, Figures 5 to 7 present highways, major roads, and the bridge network in Miami-Dade County, respectively. Figures 8-13 present visualization of the social, physical, and environmental criteria.

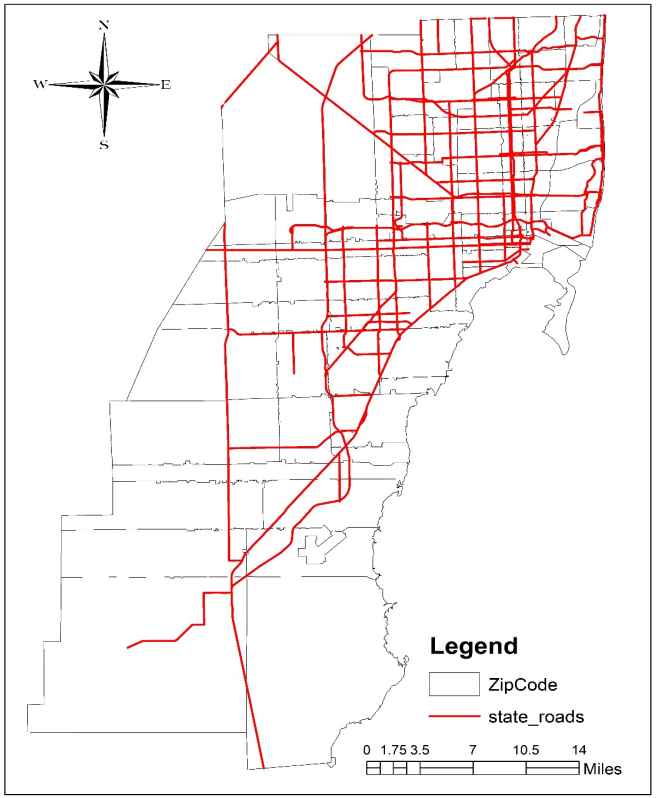


Figure 5. Miami-Dade County state roads network

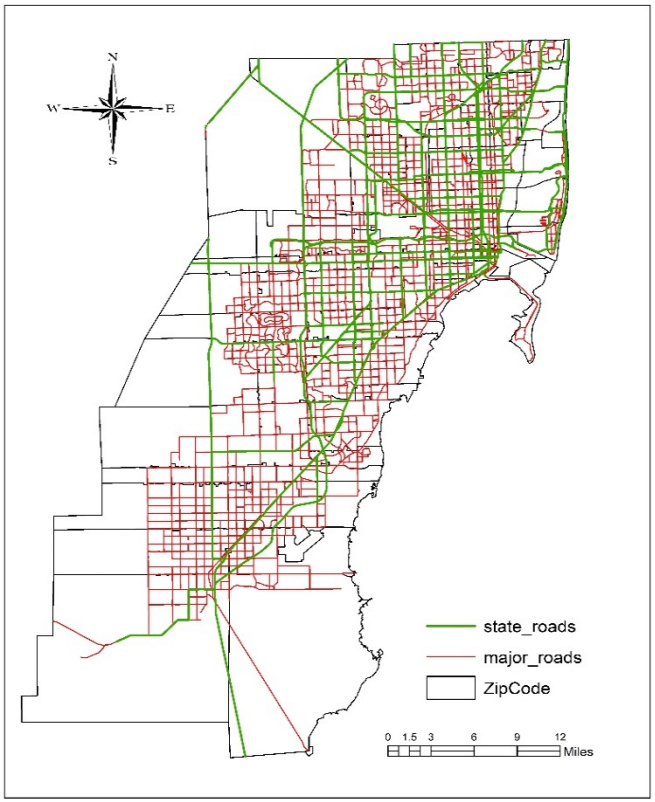


Figure 6. Miami-Dade County major roads network

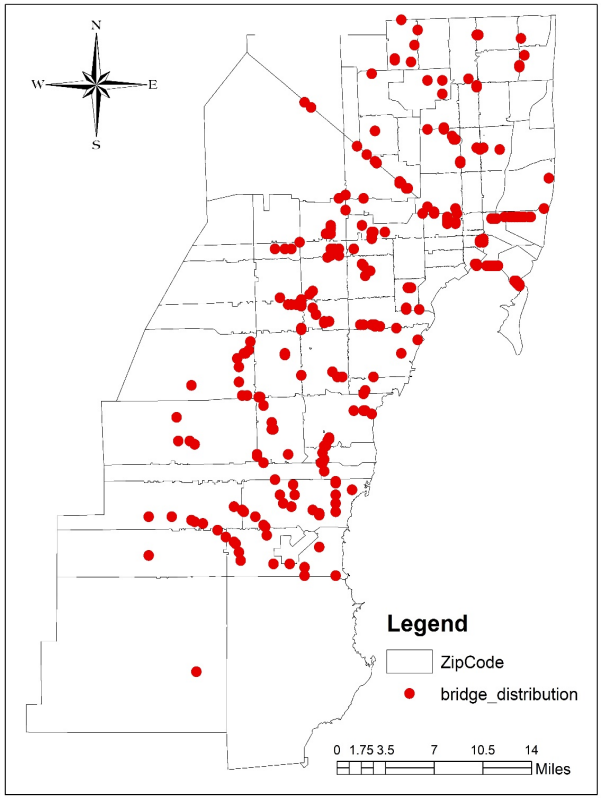
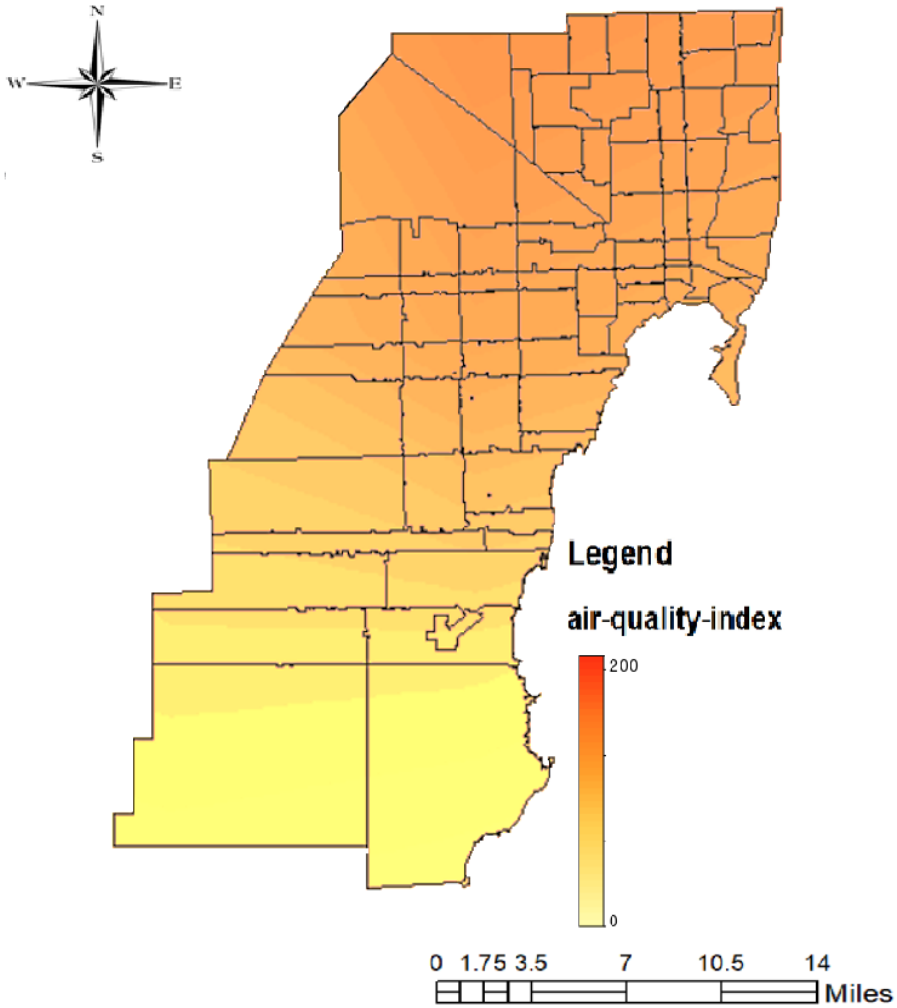
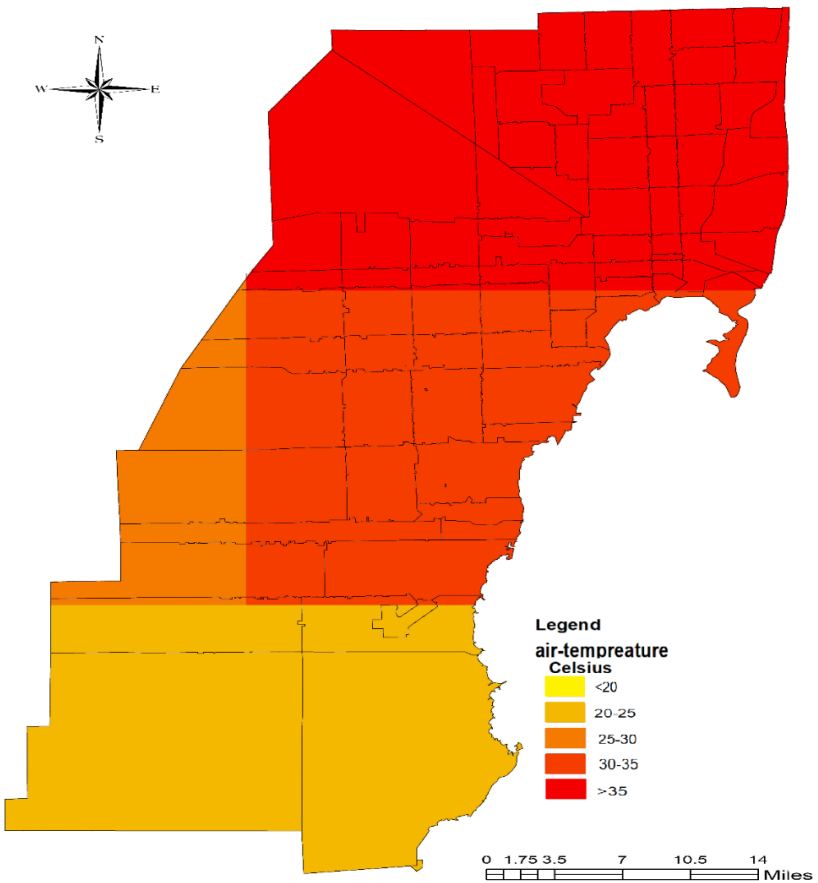


Figure 7. Miami-Dade County bridge network

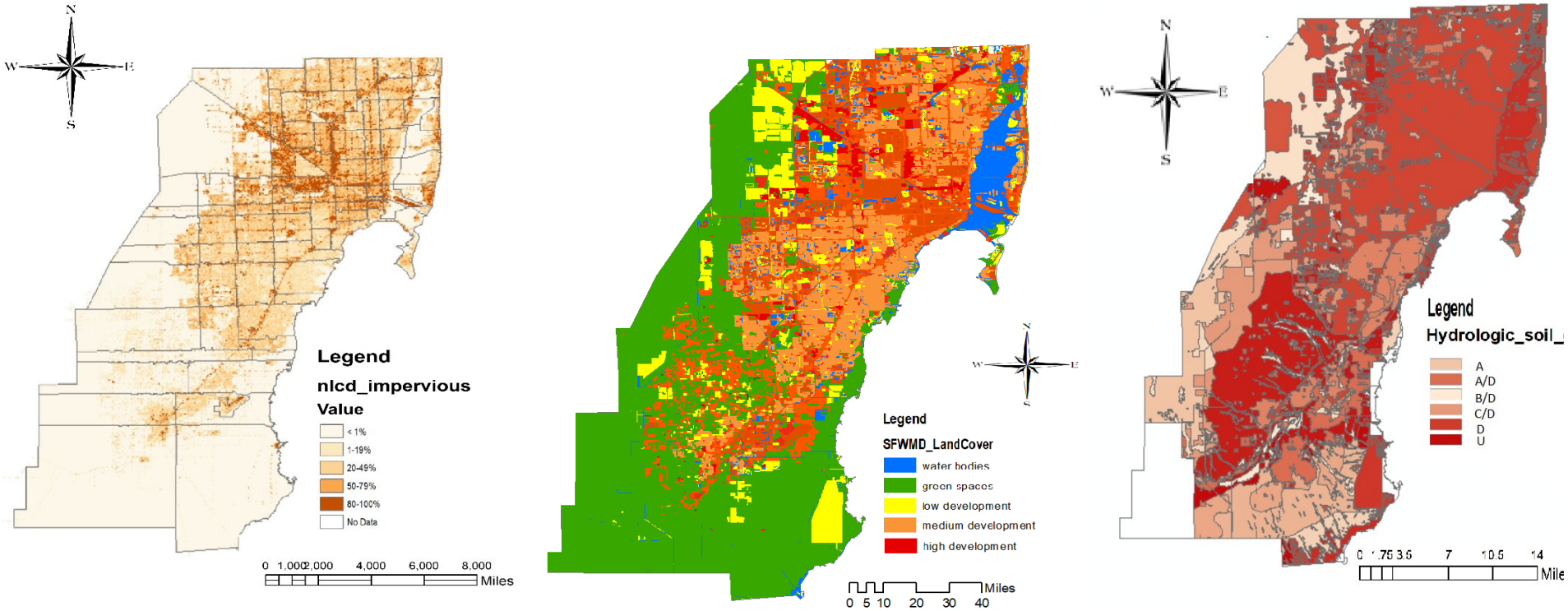


Air Quality Index, NO2



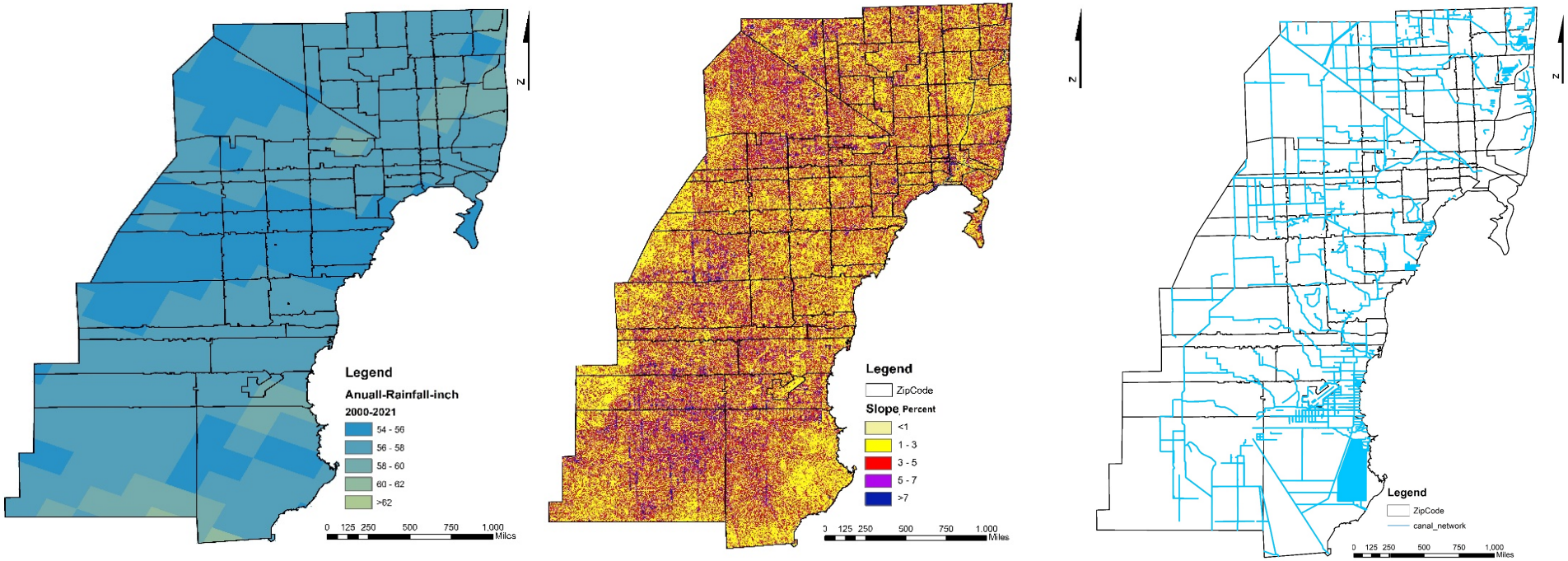
Air Temperature

Figure 8. Environmental maps



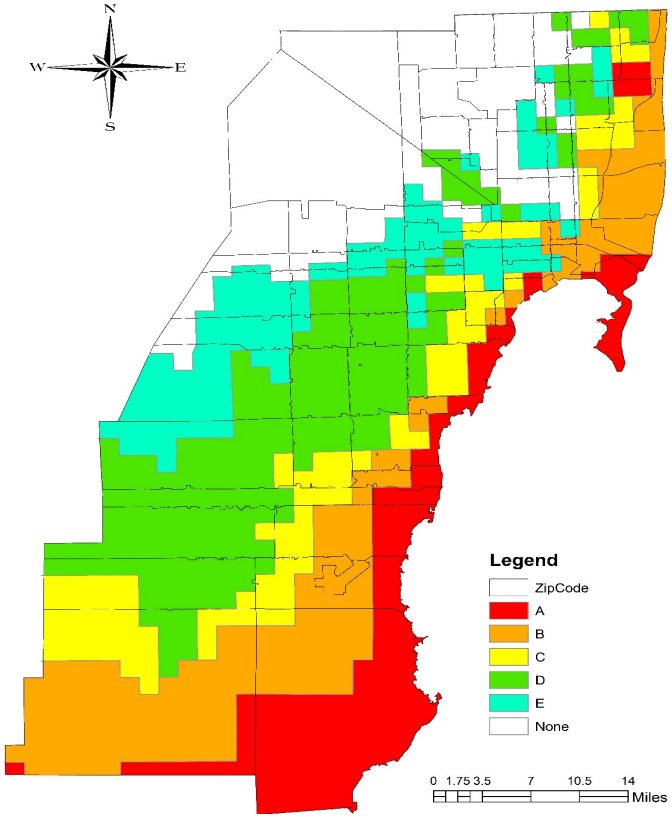
Imperviousness Land Cover Hydrologic Soil Group

Figure 9. Physical maps (Imperviousness, land cover, and hydrologic soil group)



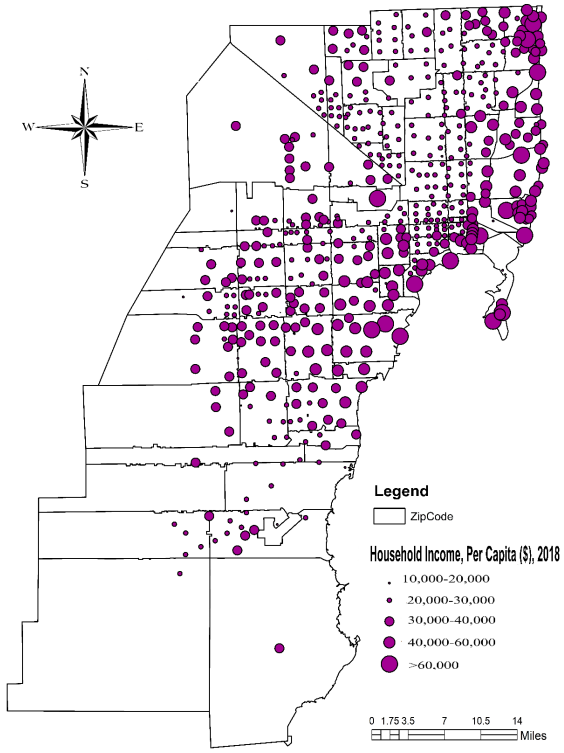
Annual Rainfall Slope Canal Network

Figure 10. Physical maps (Rainfall, slope, and canal network)

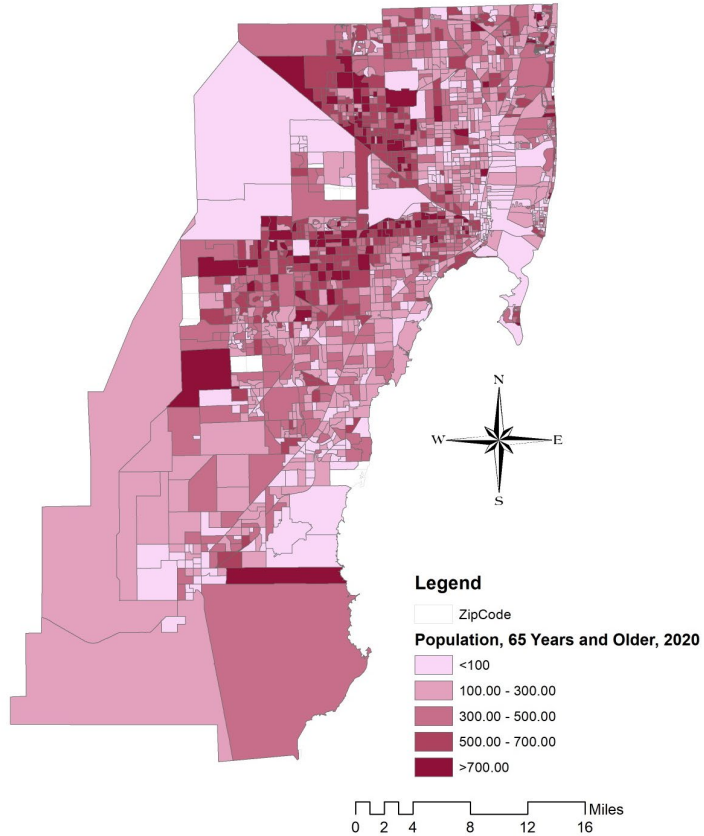


Hurricane Evacuation Zones

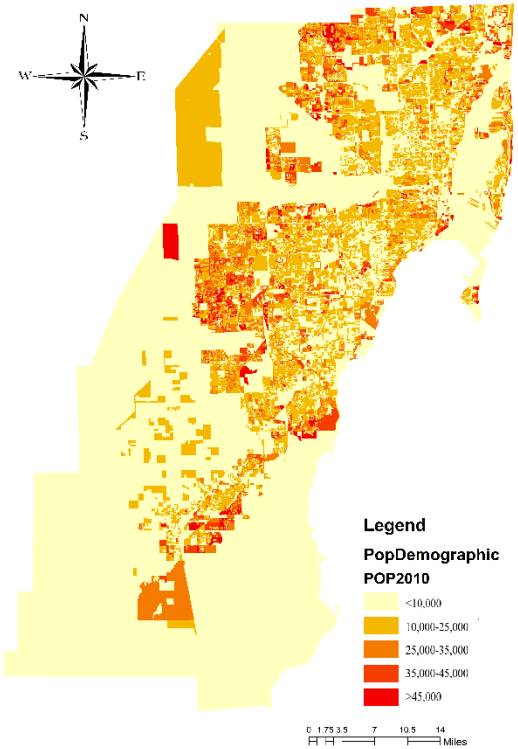
Figure 11. Physical map (Hurricane Evacuation Zones)



Household Income

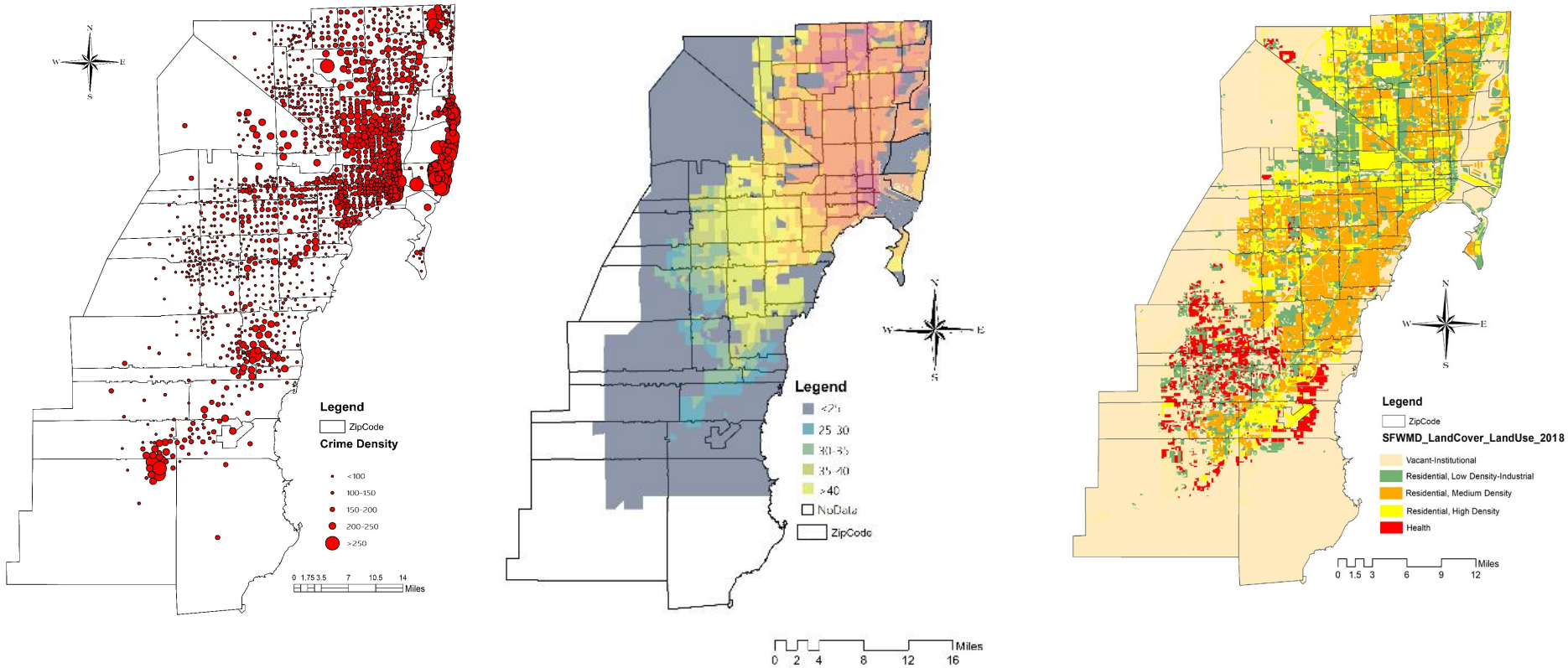


Population Density, 65+



Population Density

Figure 12. Social maps (Income and population density)



Crime Index

Average Commute Time

Land Use

Figure 13. Social maps (Crime, commute time, and land use)

Task 3- Framework Development

An effective, MCDA technique that is compatible with the problem in hand and is capable of handling group decision making will be used in GIS environment to develop the decision support framework. The details and interrelationship between the elements in the framework will be determined based on the data from Task 2. The combined risk analysis maps represent a better elaboration of the risk (hazard) zones, determine the proportions of areas subjected to varying degrees of risk factors. In this phase, all data collected would be used to develop the decision model. Integrated risk assessment maps are generated as a spatial overlay between the various given hazard data and maps.

Task 4- Spatial multi-criteria group decision analyses

The developed framework will be applied to the case study and vulnerability and risk maps will be generated.

Task 5- Reporting

The results and findings of the study will be reported in a manner consistent with existing protocols. Future directions and recommendation for applying the framework to other geographic regions will be provided in the final report.

5. Expected Results and Specific Deliverables

The proposed framework can be used as a decision support tool by state or regional decision makers in prioritizing ABC activities (e.g., accelerated upgrade/repair solutions) for existing bridges as part of the maintenance/rehabilitation programs. The framework can be leveraged to develop an online (cloud-based) decision support tool that generates vulnerability and risk maps by taking several spatial input data from the user (or automatically from public databases) and the decision maker's opinion on the relative importance of different physical, social, and environmental factors. Applicability of the framework to different geographic regions hinges on the availability of the input GIS data. Most of the input data are available for the entire country through national, state, or regional datasets. Therefore, the methodology is not limited to any specific geographic region. However, the decision-making criteria and their associated GIS data need to be determined for each study region. For example, groundwater data may be more important in coastal regions with shallow water tables compared to inland areas with deeper groundwater levels. Also, the importance of social criteria and socio-cultural/demographic data may be different when the study region houses underrepresented communities and minority groups. The project is planned for future extensions in multiple phases, providing opportunities for developing larger proposals to seek funding from other agencies. Future extensions of the project include, but are not limited to, the consideration of larger case studies (e.g., the entire bridge and road networks in Florida), incorporation of climate change effects into the framework, development of risk management scenarios in concert with ABC activities to address the identified risks, and addition of uncertainty analysis to further assist the end users (e.g., state DOTs) in practical applications. As an example, development of risk management scenarios to address the identified risks are expected to result in complementary elements in the ABC project site (e.g., implementing storm water green infrastructure to alleviate flood effects and risk of bridge scouring) or additional activities related to site preparation and geotechnical tests that can be included in bridge specifications to increase the efficiency of ABC activities.

6. Schedule

Progress of tasks in this project is shown in the table below.

Item	%
Percentage of Completion of this project to Date	60

Research Task	2021										2022	
	M	A	M	J	J	A	S	O	N	D	J	F
Task 1. Literature review												
Task 2. Data identification, collection, and analysis												
Task 3. Framework development												
Task 4. Spatial multi-criteria group decision analyses												
Task 5. Reporting												
	Work Performed											
	Work To Be Performed											

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