Uncertainty-based flood resiliency evaluation of wastewater treatment plants

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ABSTRACT

Wastewater treatment plants (WWTPs) have a significant role in urban systems' serviceability. These infrastructures, especially in coastal regions, are vulnerable to flooding. To minimize vulnerability, a better understanding of flood risk must be realized. To quantify the extent of efforts for flood risk management, a unified index is needed for evaluating resiliency as a key concept in understanding vulnerability. Here, a framework is developed to evaluate the resiliency of WWTPs in coastal areas of New York City. An analysis of the current understanding of vulnerability is performed and a new perspective utilizing different components including resourcefulness, robustness, rapidity, and redundancy is presented to quantify resiliency using a multi-criteria decision-making (MCDM) technique. To investigate the effect of certain factors of WWTPs on resiliency, uncertainty analysis is also incorporated in developing the framework. As a result, rather than a single value, a range of variation for each WWTP's resiliency is obtained. Finally, improvement of WWTPs' performance is investigated by allocating financial resources. The results show the significant value of quantifying and improving resiliency that could be used in development of investment strategies. Consideration of uncertainty in the analysis is of great worth to estimate the potential room for improvement of resiliency of individual WWTPs.

Key words | coastal areas, financial resources, MCDM, resiliency, uncertainty, WWTPs

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INTRODUCTION

Flood is one of the most devastating hazards, and often leads to excessive damage to people and infrastructures. The frequency and the magnitude of floods have increased over the last decades (Milly *et al.* 2002; Svensson *et al.* 2005; Smolka 2006; Goharian & Burian 2014; Zahmatkesh *et al.* 2014). Coastal flooding from tropical cyclones, sea level rise and hurricanes could affect many people in coastal regions that are prone to floods (Mousavi *et al.* 2011). Heavy rainfall, high tides, and human-based reasons such as inappropriate land use and increased population, as well as climate change impacts, can increase the potential for flooding (Nazif *et al.* 2012; Tingsanchali 2012; Karamouz *et al.* 2013; Goharian *et al.* 2015, 2016; York *et al.* 2015; Tavakol-Davani *et al.* 2016). There are numerous examples of devastating flood events that have led to considerable damage to communities. Examples are the floods that occurred in central Europe in 2002 and 2005, resulting in approximately 21.5 billion euros in financial damage (Kron 2005). The history of flooding in the United States also reveals that coastal areas, especially on the east coast of the USA, are highly vulnerable to floods and storms. The most recent flood events, hurricane Irene and super storm Sandy are evidence of extreme vulnerability.

Any damage to coastal cities' infrastructures caused by flood hazard can paralyze the daily lives of people. Wastewater treatment plants are among the strategic infrastructures that make water usable for end users. Cities with combined sewer systems are more vulnerable in times of floods. This is due to the serious water pollution caused by combined sewer overflows; a situation in which both

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storm water and wastewater directly discharge to waterbodies and can cause adverse environmental and socioeconomic impacts. Coastal cities and their infrastructures are becoming more prone to coastal flooding (Zahmatkesh *et al.* 2015). Gornitz *et al.* (2001) acknowledged that sea level rise and coastal erosion could make much of the New York City (NYC) coastline vulnerable to flood. Bowman *et al.* (2008) stated that because of the proximity of land to the mean sea level in NYC, hurricanes and tropical cyclones are capable of causing storm surge risks in much of the region. Considering the urbanized nature of NYC, there is added stress that flood risk threatens the natural and built environment because of the existence of critical infrastructure systems, their interdependencies and close relation with human settings.

The significant damage caused by recent floods in urban areas, such as NYC and New Orleans in the USA and European countries such as the Netherlands, indicates the need for change and review of the current understanding and methods of flood management. For this purpose, a holistic perspective that embraces various social, economic, and hydrologic features of the coastal system is needed. In previous studies, the change towards using non-structural means and measures in facing flood events can be observed. Anselmo *et al.* (1996) presented a coupling hydrological and hydraulic modeling approach for risk assessment of flood-prone areas. They applied their approach in analyzing the adverse impacts of flooding on thermoelectric power plants. Filatova *et al.* (2011) suggested different coastal management strategies to decrease potential damage, and as a result, reduce risk. They developed a conceptual model that links flood risk, the housing market, and individual risk awareness. Fu & Kapelan (2013) investigated the probabilistic dependence between rainfall depth and duration in flood risk analysis, which can play a vital role in flood risk management. Zheng *et al.* (2015) used a joint probability distribution of related factors in assessing flood risk in a coastal area.

Resiliency is a concept in flood disaster management describing the ability of a system to cope with flood, absorb the corresponding adverse impacts, and return to its normal condition (Simonovic & Peck 2013). Although there is no generally accepted meaning for resiliency, many agree that in defining it, some crucial characteristics are essential. Bruneau *et al.* (2003) were the first to give resilience a tangible meaning. They summarized resiliency in the 4Rs of robustness, redundancy, resourcefulness, and rapidity, that have been widely used by other researchers. Kendra & Wachtendorf (2003) used the concept of the 4Rs to examine the reconstruction of the Emergency Operation Center in NYC after its destruction in 2001. They proposed a method to highlight several aspects of resiliency. Their results showed that, despite the destruction of physical facilities, the organization established to manage crises in NYC could enable an effective response in terms of resiliency. Chang & Shinozuka (2004) defined a quantitative measure of resilience based on the earthquake loss estimation models for the Memphis water system in Tennessee. Considering multiple dimensions of resilience, such as technical, organizational, social, and economic, they proposed resilience measures that relate losses in future disasters to seismic performance. IPET (2009) mentioned that lack of resilience to overtopping expressly increased flooding for walls and structural components.

Cimellaro *et al.* (2010) proposed a framework for quantifying resilience using an analytical function. The proposed function considered the effect of earthquake as the disaster, the results of response and recovery, and effects of restoration and preparedness. They implemented this framework for evaluation of health care facilities subjected to earthquake in California. Zimmerman & Faris (2010) acknowledged that a deep understanding of the characteristics of critical infrastructure from the resiliency standpoint is necessary in creating future expectations and adaptation. Da Silva *et al.* (2012), using information and evidence from 10 cities, proposed a conceptual model based on resilient features to analyze urban systems in order to improve the adaptive capacity of urban populations. Simonovic & Peck (2013) presented a systems framework for quantification of resilience through system dynamic simulation. Five major factors, physical, economic, social, health, and organizational, were considered.

For quantifying resiliency, effective factors representing the system characteristics are required to be identified. Resiliency can be calculated by combining the identified factors considering their importance. Different methods based on multi-criteria decision-making (MCDM) techniques can be used for selection and ranking of the effective factors. MCDM has been used in many studies related to water resource management; for example, Raju & Duckstein (2004) used an integrated application of cluster analysis and MCDM by employing economic, environmental, and social criteria to rank water resource planning strategies in the Flumen Monegros irrigation area in Spain. Ronco et al. (2015) employed an MCDM approach to develop 300-year flood maps for several risk categories of human, cultural infrastructures, economic infrastructures, and environment in Switzerland.

There are uncertainties associated with data and model development, as well as utilizing engineering judgment (particularly when dealing with MCDM methods) to quantify performance criteria. As for flood resiliency, these uncertainties need to be quantified in order to determine the potential range of the resiliency's variation. Simonovic (2005) presented an algorithm, in which MCDM methods combined with fuzzy theory, to deal with uncertainty in water resource management. Moya et al. (2013) incorporated flood inundation uncertainties in modeling the hydraulics of the Timis–Bega basin in Romania. For this purpose, they used a cloud and cluster analyzing method. Their method was then compared with the Monte Carlo procedure in uncertainty analysis and showed the reduction of the time needed for uncertainty analysis. Alfonso et al. (2016) provided a method according to the concept of value of information (VOI) to investigate the use of uncertain information in decision-making and planning for floodplains. A VOI map, as the result, depicted floodplain regions in which additional information is required to assist spatial flood planning decision-making.

One recent example of MCDM techniques is the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) method. This method has preference in application due to its simplicity in comparison with other methods (Morais & de Almeida 2007). PROMETHEE was first introduced by Brans et al. (1984), and Brans & Vincke (1985), as a family of outranking methods for solving MCDM problems. These methods solve MCDM problems by comparing the preference relations among several alternatives to acquire information on the best alternative. Balali et al. (2014) compared the analytical hierarchy process (AHP) method with the PROMETHEE technique in selecting appropriate structural systems, and concluded that due to reasons such as its simplicity, ease of understanding, and consistency of results PROMETHEE is the preferred method. AHP, proposed by Saaty (1977, 1980), is a method used to model subjective decision-making processes based on multiple attributes in a hierarchical system (Tzeng & Huang 2011).

In this study, an approach is proposed and used to quantify the resiliency of wastewater treatment plants (WWTPs) as one of the most important services of urban systems. As a result, a better understanding of resiliency should be captured. By including hydro climatic phenomena such as surge followed by coastal flood and hurricanes, and also the loss of service due to the critical infrastructure interdependencies, this approach considers the vulnerability posed to WWTPs. Fourteen WWTPs are located in NYC. This city has experienced damaging storms of multiple proportions such as hurricane Irene and super storm Sandy. WWTPs in this cosmopolitan area have been exposed to such coastal flooding, which leads to deterioration in performance or even complete failure of these vital facilities. Hence, assessment of resiliency for this infrastructure could provide a framework to analyze and suggest how to strengthen them through physical and adaptive measures. To quantify resiliency, an index is proposed based on the four basic concepts of robustness, redundancy, resourcefulness, and rapidity. Robustness (Ro) is defined as the WWTP's intrinsic strength in facing floods without suffering considerable degradation or loss of functionality for providing a service to the public. Redundancy (Re) is the availability of alternative resources capable of satisfying the functional requirements of WWTPs in case of flood events. Resourcefulness (Rs) is the capacity to mobilize resources, prioritize, and identify problems. This factor is highly related to managerial skills to efficiently allocate financial and technological resources when flood occurs. Rapidity (Ra) is considered as the capacity of WWTPs to return to normal conditions in a timely manner.

WWTPs are compared based on the quantified values of resiliency, and their performance in dealing with flooding is investigated considering their characteristics as the factors used in development of the resiliency index. The AHP method is used for prioritizing the identified factors weighted by a group of experts. The developed method is based on the MCDM approach, and uses the weights and actual values of factors. Considering the uncertainties in determining the actual values of factors, the most appropriate probability distributions to those observed values of factors of more random nature are fitted. Consequently, the range of variation of resiliency for each WWTP is estimated. In addition, factors that can be strengthened by investment schemes are identified to improve resiliency.

The paper is organized as follows. The details of methodology are described in the next section. Then, a comprehensive analysis of the wastewater treatment plants in NYC is presented. Finally, the results are discussed followed by a summary and conclusion.

METHODOLOGY

In order to develop the system's framework, the 4R criteria of resiliency are utilized. The proposed framework is a parametric approach based on the characteristics of the WWTPs that are effective on flood consequences. Therefore, at the first step, a list of quantifiable factors that are related to the performance and resiliency of WWTPs in times of flooding is prepared (Karamouz & Nazif 2013; Zahmatkesh 2014; Karamouz & Zahmatkesh 2016). These factors are from different data types, such as hydrological, social, economic, and technical. Then, actual values for the identified factors are collected. The considered factors (sub-criteria) are presented in Table 1. Based on the definition of the 4Rs of resiliency, it also determines partitioning resiliency into four different criteria, and which sub-criterion belongs to which criteria.

Considering the 4R term of resiliency and in order to assist in developing the resiliency index, a methodology flowchart is developed and presented in Figure 1.

Table 1 | Different sub-criteria for WWTPs to quantify flood resiliency

Resiliency term (criteria)	ID	Sub-criteria description	Unit
Rapidity	Ra_1	Hurricane flood elevation (based on North American Vertical Datum of 1988 (NAVD88))	ft
	Ra_2	Adverse environmental impacts on the surrounding area (due to treatment failure because of flooding)	–
	Ra_3^a	Plant design capacity (a function of the plant users)	MGD[b]
	Ra_4	Post-stress recovery (refers to any disaster management plan after the flood disaster)	hour
	Ra_5	Population served (number of residents that are served by the plant)	#
Robustness	Ro_1	Additional load in time of flooding (the difference between WWTP capacity for the total maximum wet and dry weather flow. Maximum wet weather flow is the maximum flow received during any 24 hour period. Maximum dry weather flow is the maximum daily flow during periods without rainfall)	MGD
	Ro_2	Critical flood elevation (100-year flood elevation +30 inches for expected sea level rise by the 2050s, which is determined based on the Federal Emergency Management Agency's new advisory base flood elevation maps for a 100-year flood event, was selected as the baseline for the analysis)	ft
	Ro_3	Maximum inundation depth (due to the flat terrain of the plant, several areas may be flooded by up to this value of water during the critical flood event)	ft
	Ro_4^a	Percent of not-at-risk equipment (percent of plant items that are not at risk of damage during flood)	%
	Ro_5	DMR violations (the percentage of discharge monitoring reports that resulted in effluent violations. During minimal levels of stress, the DMR violation percentages are indicative of how well each treatment plant can cope with daily operational stresses)	%
	Ro_6	Damage cost from the most severe historical hurricane (without flood protection for the plant)	$
Resourcefulness	Rs_1^a	Number of plant technical staff	#
	Rs_2^a	Availability of dewatering facilities (facilities to drain sludge to decrease 90% of its liquid volume)	–
	Rs_3	Total risk avoided for every single dollar spent over 50 years	$
Redundancy	Rd_1	Existence of underground tunnel systems	–
	Rd_2	Availability of WWTPs in the neighboring areas (distance from the closest WWTP)	ft
	Rd_3^a	On-site storage (volume of lakes in the WWTP's zone)	ft^3

[a]Sub-criteria with investment potential to improve.
[b]Million gallons per day.
1 ft = 0.3048 m, 1 gallon = 3.78 litres, 1 inch = 2.54 cm.

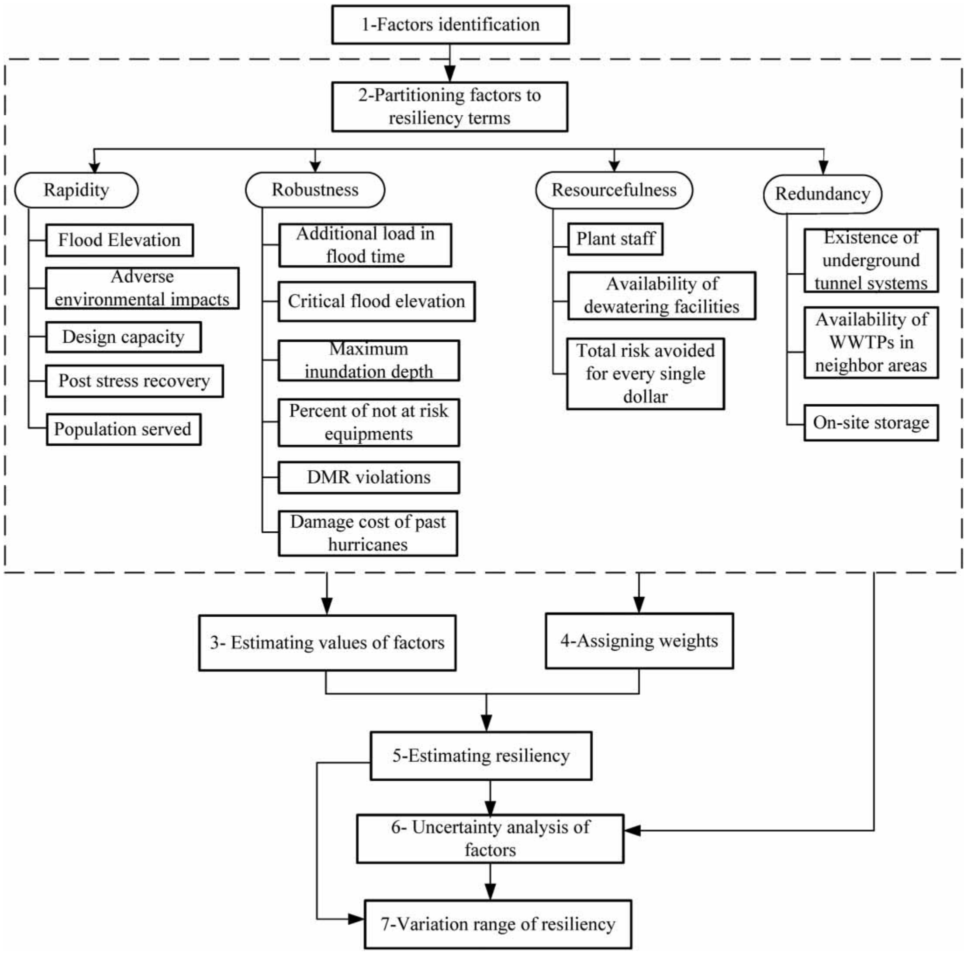

Figure 1 | Proposed framework for quantifying resiliency of wastewater treatment plants.

After determining the effective factors' values, WWTPs' characteristics (factors) are weighed based on their role and importance in the performance of the WWTP in dealing with floods. As a main step, it is determined which factor (as a sub-criterion) belongs to which resiliency term (i.e., Ra, Ro, Rs, and Rd) as the criterion. The 4Rs of resiliency are also weighted based on the assigned weights to sub-criteria and, along with the actual values and weights of the sub-criteria, are used to quantify WWTP resiliency. An index is developed for this purpose. A number of WWTPs are considered and then compared based on the quantified values of resiliency.

Factors' representation

In order to characterize a WWTP and determine its resiliency, varieties of factors are identified and used (Table 1). To obtain the actual values for the factors presented in Table 1, different official reports including Bloomberg & Strickland (2013) and NYCDEP (2013) are used. In Table 1, factors with the potential to be improved by financial investment are also determined. These factors are used for further analysis.

Weighing criteria and sub-criteria

On the surface, the criteria of robustness (Ro), redundancy (Re), resourcefulness (Rs), and rapidity (Ra) appear equally tied to quantify resiliency for an urban infrastructure such as a WWTP. However, the weight of these criteria could not be the same. Robustness and rapidity can be regarded as the 'ends' of resiliency. In other words, in order to describe the extent to which a WWTP is resilient, the criteria of both (Ro and Ra) must be fulfilled (i.e., these criteria could be considered as the final objectives for a resilient system). Robustness describes the strength of the WWTP and its ability to withstand a certain level of flooding without suffering degradation or loss of function of treatment of the wastewater. On the other hand, rapidity describes the ability of the system to meet goals and priorities in a timely manner in order to avoid disruption of service. Therefore, together, these two terms can represent the ends of resiliency for a WWTP. If the estimations of the WWTP's robustness and rapidity are both high, then it could be considered resilient. Moreover, redundancy and resourcefulness are means by which the system can become more resilient. These 4Rs are all terms of resiliency that should be taken into account when quantifying the resiliency of a system. Considering the text mentioned above, based on the system of interest, the importance (weight) of the 4Rs could be different.

Appropriating more resources and doing so in an efficient manner will increase the capacity of the system and, in turn, will also increase the resiliency. If the system is more resilient, then it will perform more closely in the way that was intended. In terms of the 4Rs, a WWTP is considered resilient if it can both manage the incoming raw wastewater load and also treat it to a particular quality level standard before discharging it as effluent.

Based on the main functions of WWTPs, in this study, weights for the four terms of resiliency are determined. If the resiliency of the infrastructure can be quantified, it would give stakeholders the opportunity to see a clearer picture of vulnerability. In addition, resources could be more efficiently allocated with the aim of increasing flood resiliency.

The relative importance (weight) of the factors is determined in the form of a questionnaire survey. For this purpose, a questionnaire was designed, and in order to get the best reliable information from the survey, experts were asked to complete it based on their engineering judgment. These experts were selected among a group of people that were well familiar with the concept of flood resiliency in WWTPs (including four professors, two practitioners, and one post-doctoral fellow). The experts were selected from different ages (30 to 65 years) and career lengths (10 to 30 years) as an indicator of their level of experience. The experience and the knowledge level of the experts were different. However, their understanding of the system's resilience against flooding was sufficiently adequate to be selected for this study. We could only locate a limited number of respondents due to the fairly new resiliency concept used in this study. We believe that the selected pool of respondents has provided answers from different perspectives. These answers are considered adequate to develop the methodology; however, a larger pool of respondents is needed for actual implementations. The questionnaire sample is similar to what is presented in Table 1, with an additional column to record the assigned weight by the expert (see Appendix, available with the online version of this paper). The weights assigned to each sub-criterion by different experts are combined to obtain a relative weight (w) for the sub-criteria. The weight of each sub-criterion indicates the overall importance of that to the flood resiliency of a WWTP. The higher the weight (e.g., a maximum of 10), the more important the sub-criterion is. The factors are compared on a scale of 1–10 where 1 and 10 indicate very low and very high importance, respectively.

Resiliency index

For development of a resiliency index, actual values of WWTPs' sub-criteria and their corresponding weights are used in a model developed utilizing the MCDM method. For this purpose, several governing equations (described later) are formulated. Based on the general concept of this method (where subjective information is used), resiliency could be quantified by summation of normalized weights times the normalized values of some factors. In the PROMETHEE approach, this general concept for more than one alternative (WWTP facility in this study) utilizes geometrical analysis to compare the values of each sub-criterion (factor) with the corresponding values for other alternatives to provide a better means of combining subjective (weights) and objective (value) data. The developed model uses the PROMETHEE method, which is based on MCDM. MCDM can be used to solve problems involving more than one alternative (different WWTPs in this study). MCDM problems typically consist of having to pick between a numbers of options. When given a set of alternatives, an MCDM framework can allow a more informed decision to be made. MCDM is particularly useful because a set of criteria may be inherently conflicting, and the best alternative may not be so readily obvious. Since criteria could be conflicting, and since a greater preference for one sub-criterion over another may be desired, MCDM requires assignment of a relative importance to each sub-criterion. For this purpose, pairwise comparison for every combination of sub-criteria to appropriately weight the criteria is used.

Pairwise comparison

AHP method is used in order to determine the weights of the selected sub-criteria of the WWTPs based on the obtained information from the survey. AHP is an MCDM method that is based on pairwise comparison. This approach uses scaled numbers, expressing individual judgments, to reach preferences among the set of sub-criteria. In this method, pairwise judgments are based on the individual's knowledge and experience. Inconsistency of judgments in AHP is determined by calculating the inconsistency ratio. This ratio is used to capture the bias in allocating weights on different sub-criteria. It has been well described in the literature since being presented. Based on Saaty (1977), an inconsistency ratio of less than 0.10 is acceptable for evaluation purposes.

Governing equations

The developed MCDM model is based on the pairwise comparison for each characteristic of WWTPs. WWTPs' characteristics have different units and order of magnitudes. Conversion of these characteristics to comparable non-dimensional numbers is considered in the developed model. Since different WWTPs are considered to be compared, different values would be available for each sub-criterion. For a specified sub-criterion, the difference between the evaluations of any two pairs is denoted by D (negative and positive signs matter in the calculation of D). For instance, $D(f_i, f_j)$ is calculated as $f_i - f_j$ and in a similar way $D(f_j, f_i)$ is calculated as $f_j - f_i$, where i and j signify the i^{th} and j^{th} WWTP, respectively, and f represents the actual value of the factor (sub-criterion). Equation (1) is used to scale the value of D between 0 and 1.

$$\bar{D}_n(f_i, f_j) = \frac{D_n(f_i, f_j) - D_{n,min}}{D_{n,max} - D_{n,min}} \ \forall n \in N \text{ and } i, j \in M \tag{1}$$

where $D_n(f_i, f_j)$ for n^{th} factor is calculated as $f_i - f_j$ and i and j stand for WWTPs. $D_{n,min}$ and $D_{n,max}$ represent the minimum and maximum values among the differences calculated for the n^{th} factor. N signifies the total number of factors identified for evaluation of resiliency and M shows the total number of WWTPs.

The resiliency index for the i^{th} wastewater treatment plant ($\mathrm{Res_i}$) is calculated as follows:

$$\mathrm{Res_i} = \left(\sum_{n=1}^{N} \left(\frac{1}{M-1} \times \sum_{j=1}^{M} \left(\bar{D}_n(f_i, f_j) - \bar{D}_n(f_j, f_i) \right) \right) \times w_n + 1 \right) \times 50 \tag{2}$$

where $i = 1, 2, \ldots, M, i, j \in M$ and w_n shows the weight of the n^{th} sub-criterion. The value of $(1/M - 1 \times \sum_{n=1}^{N} (\bar{D}_n(f_i, f_j) - \bar{D}_n(f_j, f_i)) \times w_n)$ in Equation (2) varies between -1 and 1. By adding a unit value (1), this value is rescaled between 0 and 2. Then, the equation is multiplied by 50 for rescaling the result between 0 and 100. It should be noted that Equation (2) is the linear form of the PROMETHEE method, which assumes linearity between resiliency and rescaled actual values.

It should be noted that the resiliency of WWTPs is also obtained with a decision-making-based method using software called D-Sight (http://www.d-sight.com/). This software uses the PROMETHEE as a geometrical analysis for an interactive decision aid to combine subjective and objective data, and presents an approach for quantifying resiliency.

Improving resiliency

In order to increase WWTPs' resiliency against flooding, financial resources can be allocated to improve relevant functions/factors. Since the resiliency index is calculated based on the estimated actual values, sub-criteria with financial investment potential to improve resiliency (indicated in

Table 1) can be targeted. This is of particular use especially for WWTPs with low values of resiliency.

Various scenarios (presented in the Results section) are proposed and compared to assess how they can increase resiliency spending certain financial resources. For each scenario, the amount of money that is needed for increasing each economic-based sub-criterion for one unit is estimated based on the data sources. Then, the effect of increasing the actual values of the selected sub-criteria on improving resiliency is investigated. Increase in the actual values for multiple factors is also considered.

Uncertainty analysis

Values of resiliency that can be obtained from Equation (2) are based on initial estimated values of factors for WWTPs. Although these values are acquired based on the interpretation of the official reports, they could be subject to error and uncertainties arising from the method used for their determination. Therefore, there is uncertainty associated with data availability and accepting representative values of sub-criteria using engineering judgment, and also accepting minimum and maximum values of sub-criteria for WWTPs as the lowest and highest values. One of the important parts of this study is the determination of the variability of the estimated actual value of each sub-criterion. Monte-Carlo simulation is used in this study for uncertainty analysis.

Monte Carlo simulation is a numerical procedure to reproduce random variables that preserve the specified distributional properties (Tung & Yen 2006). In Monte Carlo simulation, the response of the system of interest is repeatedly measured under various system parameter sets generated from the known or assumed probabilistic distributions. It offers a practical approach for uncertainty analysis because the random behavior of the system response can be probabilistically duplicated. Therefore, each factor is assumed to be a random number with a certain distribution. This distribution can be estimated based on the observed values of that factor for all WWTPs. Not all of the sub-criteria could be treated as random numbers; therefore, a number of them are selected for this part of the analysis. By generating random numbers of selected sub-criteria actual values based on the determined distributions, the variation of resiliency for each WWTP could be obtained. This variation is useful for resiliency improvement, because it provides a range of variation from our initial estimates. Furthermore, it provides a framework for investigating how resiliency can be improved by improving the values of sub-criteria (depending on whether increasing or decreasing them is preferred).

CASE STUDY

The case study is NYC, which has experienced several storm events in recent years. Extratropical cyclone Sandy was a turning point. After this destructive super storm, some critical infrastructures of NYC, such as transit systems, were inundated and shut down for days, revealing the susceptibility of the megacity's infrastructure to coastal flooding (Kokoszka 2013). The Metro Hurricane Transportation Study (US Army Corps of Engineers 1995) describes some alarming issues about flood risk in NYC. For example, it was claimed that if a storm occurs it may produce surges of up to 30 feet above mean sea level in some parts of the city. Super storm Sandy shows a clear link between the risk caused by a hydro climate hazard and the load imposed on city infrastructure.

WWTPs in NYC remove 90% of pollutants from 1.3 billion gallons of wastewater on a daily basis. Treatment plants are vital in protecting the environment and public health, as they are essential to providing clean waterways and bathing beaches. Resiliency of a treatment plant and how to increase it is the main challenge in this study. Plants' locations, names, and their service area boundaries on the NYC map are shown in Figure 2. These WWTPs experienced either partial or complete disruption of service during and after extratropical storm Sandy (Kokoszka 2013). In addition to data for Sandy, available operational data for the treatment plants are also used to perform the analysis.

According to Figure 2, every part of the case study drainage area belongs to only one WWTP (it should be noted that this is a combined sewer system); therefore, there is no interrelation between plants.

RESULTS

In Table 2, actual values of the sub-criteria for different WWTPs are presented. In order to calculate the weights of each sub-criterion, the normalized weights of 17 sub-criteria

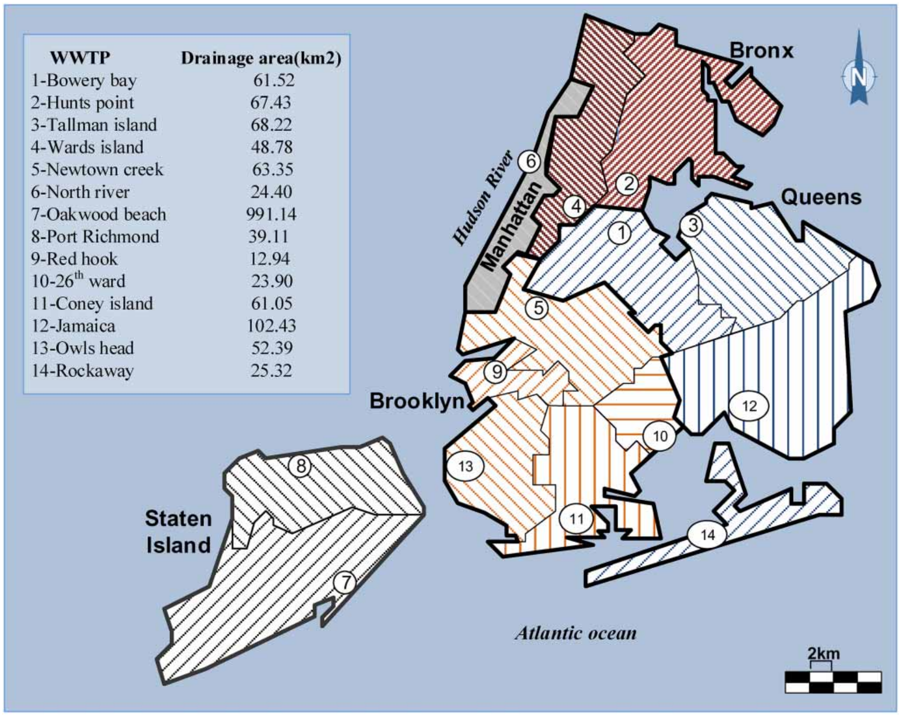

Figure 2 | Study area and the location of 14 wastewater treatment plants with the corresponding service areas (adapted from NYCDEP 2013).

are calculated using pairwise comparison through the AHP method. The weight of each criterion (i.e., 4Rs) is then calculated as the summation of all the corresponding sub-criteria weights. These weights are normalized so that the summation of the weights for the 4Rs criteria would be 1. In Table 3, the weights (relative importance) of sub-criteria and criteria are presented. These weights are obtained by post-processing the weights assigned to the factors by the experts.

Based on the results in Table 3, it can be observed that rapidity and robustness are weighed more than resourcefulness and redundancy. After analyzing the alternatives (WWTPs), the proposed MCDM method ranks WWTPs' facilities. Owing to the way in which the criteria are determined, the resulting output gives a relative resiliency index for each wastewater treatment plant. The results are shown in Figure 3.

Based on Figure 3, the most resilient treatment plants according to the proposed method are Wards Island, Jamaica, and North River. On the opposite side, the least resilient treatment plants are Rockaway, Hunts Point, and Oakwood Beach. This is in agreement in most parts by the report prepared by NYCDEP (2013). It is also observed that the resiliency results obtained by the proposed technique and based on the D-Sight method are similar.

By improving the actual values of sub-criteria through investment, the resiliency of WWTPs could be improved. Those sub-criteria with high weights (based on the ranking results) and low values (in comparison with the minimum and maximum historical values) are preferable for investment; because not only do they have more effect on the resiliency value due to their weights, they also have a great potential for improvement.

Uncertainty analysis

In order to incorporate the scheme proposed in the Methodology section, the following steps are taken:

- The sub-criteria that can act as random numbers or have an uncertain nature must be recognized. Among the considered factors, sub-criteria related to hydrologic features such as hurricane flood elevation, and sub-criteria that could have an effect on flood risk such as 'percent of

Table 2 | Actual values of sub-criteria for WWTP facilities

WWTP	1. Bowery Bay	2. Hunts Point	3. Tallman Island	4. Wards Island	5. Newtown Creek	6. North River	7. Oakwood Beach	8. Port Richmond	9. Red Hook	10. 26th Ward	11. Coney Island	12. Jamaica	13. Owls Head	14. Rockaway
Sub-criteria														
Hurricane flood elevation (Ra_1) (ft)	11.6	10.2	10.1	10.7	10	9.7	13.1	12.1	11.7	12.6	10.1	0	13.5	11.4
Adverse environmental impacts (Ra_2) (-)	0	1	0	0	0	0	0	0	0	1	1	1	0	1
Plant capacity (Ra_3) (MGD)	150	200	80	275	310	170	39.9	60	60	85	110	100	120	45
Post-stress recovery (Ra_4) (hour)	0	30	3	0	13	14	167	17	0	30	112	0	16	180
Number of residents served (Ra_5) (#)	848,328	684,569	410,812	1,061,558	1,068,012	588,772	244,918	198,128	192,050	283,428	596,326	728,123	758,007	90,474
Additional load in flood time (Ro_1) (MGD)	150	200	40	275	390	170	80	60	60	85	110	100	120	45
Critical flood elevation (Ro_2) (ft)	15.5	17.5	15.5	17.5	13.5	12.5	16.5	14.5	14.5	13.5	15.5	13.5	14.5	14.5
Minimum inundation depth (Ro_3) (ft)	5	7	7	6	4	6	5	4	6	5	3	0	4	7
Percent of not-at-risk equipment (Ro_4) (%)	0.64	0.45	0.66	0.98	0.92	0.66	0.85	0.55	0.72	0.78	0.73	0.99	0.71	0.62
DMR violations (Ro_5) (%)	0	0.2	1.6	1.4	0.9	0.3	2	1.9	0	1.1	2.1	0.9	1.4	1.9
Damage cost from the most severe historical hurricane (Ro_6) ($)	112.6	201.36	45.18	8.73	28.79	94.1	20.97	54.85	67.38	82.42	84.95	1.7	48.41	49.28
Number of plant technical staff (Rs_1) (#)	81	108	71	118	88	109	59	46	55	93	69	66	68	41
Availability of dewatering facilities (Rs_2) (-)	1	1	1	1	0	0	1	0	1	1	0	0	0	0
Total risk avoided for every single dollar (Rs_3) ($)	1.71	10.14	2.97	27.33	1.03	25.99	8.3	5.8	1.34	9.71	22.59	2.19	13.78	13.1
Existence of underground tunnel system (Rd_1) (-)	1	0	1	0	1	0	1	1	1	1	1	0	1	1

(*continued*)

Table 2 | continued

WWTP	1. Bowery Bay	2. Hunts Point	3. Tallman Island	4. Wards Island	5. Newtown Creek	6. North River	7. Oakwood Beach	8. Port Richmond	9. Red Hook	10. 26th Ward	11. Coney Island	12. Jamaica	13. Owls Head	14. Rockaway
Availability of WWTPs in the neighboring area (Rd_2) (ft)	2.47	3.75	3.87	5.08	6.76	6.46	9.7	9.7	4.27	6.04	10	6.04	8.19	8.61
On-site storage (Rd_3) (ft^3)	6,415,897.6	0	2,231,592	14,445,321	0	16,254,252	1,475,604.9	9,177,280.9	4,290,165	0	0	1,588,950	2,037,387	53,459.34

not at risk equipment (the percentage of equipment that is not at risk of flooding, for example, due to a high elevation or being water proofed)' are considered as factors with an uncertain nature. Table 4 shows the complete list of the identified uncertain factors.

- The probability distribution functions for each sub-criterion's permissible values are obtained. This is done by examining different distributions such as normal, log normal, and Weibull, and then determining the best distribution function to fit to observed values of each sub-criterion for the 14 WWTPs. In Table 4, distribution functions and the corresponding parameters fitted to different sub-criteria are also presented.
- Based on the fitted distribution functions, 100 random values are generated for selected sub-criteria, and the resiliency values for 14 WWTPs are recalculated. The data generation yields 100 resiliency values for each WWTP.

Figure 4 shows the range of resiliency variation and resiliency based on actual estimated values (see Figure 3).

As can be seen, the initial values of resiliency for some of the WWTPs, such as Jamaica and North river, are near the upper limit of the variation range. This shows that the recorded actual values of sub-criteria for these WWTPs were high relative to the maximum historical values observed for sub-criteria. Considering the values of sub-criteria (that are relatively high) for these WWTPs, their resiliency cannot be increased further because there is little room for improvement. On the contrary, WWTPs with initial resiliency value near the lower limit of the variation range, such as Newtown creek, Hunts point and Rockaway, have the potential for improvement. It also indicates that the recorded actual values for these WWTPs were underestimated in comparison to the other WWTPs. For these WWTPs, by increasing the actual values of the sub-criteria, there is some room for improving resiliency. It should be noted that the uncertainty analysis of weights is not performed in this study because it was not within the scope of this work and needs a relatively large number of experts for weighting factors. However, it is suggested that it be considered for extension of this study or for actual implementation of the methodology.

Based on the 100 generated values of resiliency for each WWTP, the most appropriate distributions are fitted

Table 3 | Weights of criteria and sub-criteria

Rapidity (Ra)		**Robustness (Ro)**		**Resourcefulness (Rs)**		**Redundancy (Rd)**	
$W_{Ra}=0.302$		$W_{Ro}=0.273$		$W_{Rs}=0.205$		$W_{Rd}=0.218$	
Ra_1	0.083	Ro_1	0.046	Rs_1	0.037	Rd_1	0.065
Ra_2	0.019	Ro_2	0.083	Rs_2	0.074	Rd_2	0.046
Ra_3	0.083	Ro_3	0.028	Rs_3	0.028	Rd_3	0.037
Ra_4	0.074	Ro_4	0.037				
Ra_5	0.083	Ro_5	0.089				
		Ro_6	0.088				

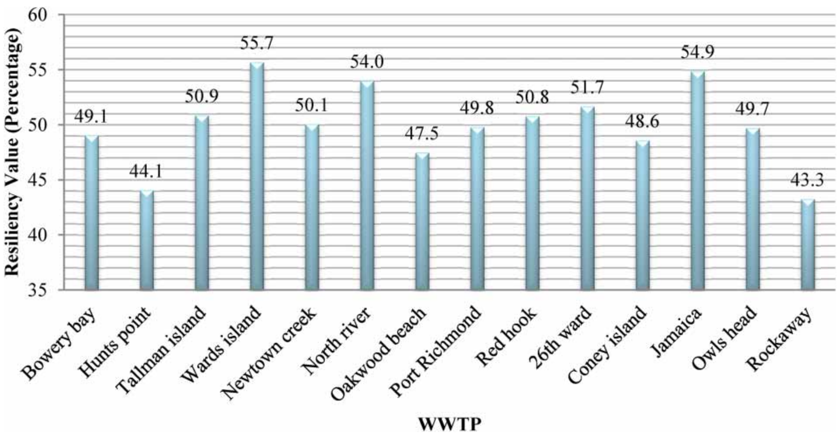

Figure 3 | Quantified resiliency index for different WWTPs.

Table 4 | Fitted distributions to the sub-criteria with an uncertain nature

Sub-criteria	**Distribution**
Ra_1 (Hurricane flood elevation)	Nakagami[d] ($a^a = 7.248$ $b^b = 119.79$)
Ro_1 (Additional load in time of flooding)	Generalized extreme value ($a = 0.30095$ $b = 52.524$ $c^c = 82.361$)
Ro_2 (Critical flood elevation)	Weibull ($a = 10.821$ $b = 15.377$)
Ro_3 (Maximum inundation depth)	Generalized extreme value ($a = -0.75455$ $b = 2.091$ $c = 4.7072$)
Ro_4 (Percent of not at risk equipment)	Lognormal ($a = 0.21304$ $b = -0.333$)
Ro_5 (DMR violations)	Generalized Pareto ($a = -1.4076$ $b = 3.6558$ $c = -0.39702$)
Rs_3 (Total risk avoided)	Generalized Pareto ($a = -0.18964$ $b = 13.557$ $c = -0.96838$)

[a]Shape.
[b]Scale.
[c]Location.
[d]Nakagami is a distribution similar to gamma distribution.

to investigate the occurrence probability of resiliency values obtained for the WWTPs. The fitted distribution functions and statistics for the WWTPs are shown in Table 5.

It should be noted that the values of resiliency for the plants with high standard deviations (σ) are more uncertain than those with lower σs. Therefore, for example, estimated resiliency values for Bowery bay are less probable than those with lower standard deviations.

Improving resiliency

The WWTPs with low values of resiliency (near to the minimum value of the resiliency variation range as shown in Figure 4) are more important to be considered for allocation of financial resources. The cost of increasing economic-based sub-criteria for one unit of cost is shown in Table 6. The data in Table 5 are obtained from data sources such

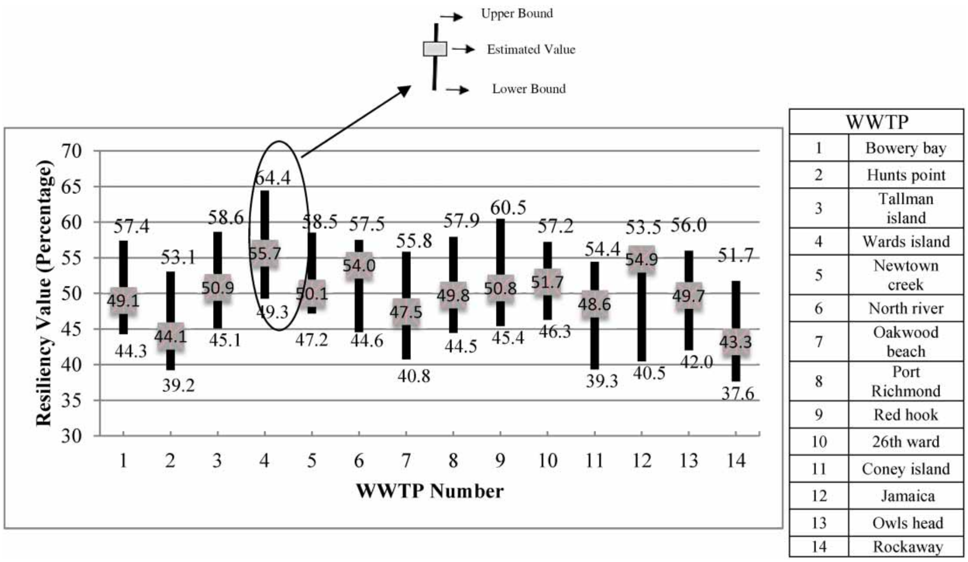

Figure 4 | Range of resiliency variation for each WWTP.

Table 5 | Fitted distributions to the resiliency values for WWTPs

WWTP	Distribution	Parameters σ	μ	
1. Bowery bay	Normal	4.303	59.674	
2. Hunts point	Logistic	2.609	50.203	
3. Tallman island	Normal	4.797	50.059	
4. Wards island	Gen. extreme value	4.126	48.318	K = − 0.358
5. Newtown creek	Gen. extreme value	4.454	47.885	K = − 0.360
6. North river	Normal	4.873	5.424	
7. Oakwood beach	Normal	3.787	49.601	
8. Port Richmond	Normal	4.469	49.987	
9. Red hook	Lognormal	0.072	3.910	γ = 0
10. 26th ward	Normal	4.139	50.523	
11. Coney island	Normal	3.927	3.927	
12. Jamaica	Lognormal	0.029	4.860	γ = − 78.419
13. Owls head	Logistic	2.523	50.639	
14. Rockaway	Gen. extreme value	5.081	49.657	k = − 0.427

Table 6 | Cost of increasing sub-criteria with investment potential

Sub-criteria	Unit	Cost of increase for one unit
Plant design capacity (Ra_3)	MGD	\$10 m per million gallon
Number of plant technical staff (Rs_1)	–	\$0.043 m for each staff annual wage (21\$ hourly wage)
Percent of not-at-risk equipment in each WWTP (Ro_4)	%	\$1.750 m for elevating and water proofing electrical equipment
Availability of dewatering facilities (Rs_2)	–	\$7 m
On-site storage (Rd_3)	ft^3	\$4.5 × 10^6 m for excavating $1ft^3$

as the EPA (Environmental Protection Agency) and sites such as www.bls.gov, as well as engineering judgment and consultation with experts. The initial analysis of the results shows that at least a 30% increase in the actual values is required for improvement of resiliency. It should be noted that in estimating the effect of financial investment on the 'Percent of not at risk equipment in each WWTP', shown as factor Ro_4, in the absence of any related data it is assumed that 20% of at risk equipment falls into the electrical category that can be placed at a higher elevation, and its submergence capability enhanced. Based on this assumption, improvement in Ro_4 can be as much as 30%.

Table 7 provides the descriptions of six defined scenarios. Based on the results provided in Figure 4, the effect of implementing these scenarios to improve the resiliency of Rockaway, as an example which has the lowest resiliency value among the considered WWTPs, is investigated.

DISCUSSION

As can be seen in Table 7, scenario numbers 1, 6, and 7 require an extremely high cost value compared to the others, which makes these options impractical. The high cost of structural expansion is the main reason for the high cost of these scenarios. Considering the results presented in Table 6, it can be concluded that, in general, structural measures are expensive to implement and cannot considerably improve the resiliency. However, non-structural measures, such as increasing plant staff, are cost-effective and consequently are preferred for use. In terms of recovery from flooding, the return to normal plant operations can be attributed to the plant staff when they try to reduce the amount of damage to critical equipment. According to NYCDEP (2013), plant staff could undertake many precautionary tasks, such as sandbagging low-lying buildings, relocating some of the portable equipment, filling chemical tanks, making sure that emergency power equipment is operational, and shutting down certain inflow pipes to reduce the inflow of combined sewage to the plant. By comparing scenarios regarding the percent of increase in the resiliency and the estimated costs, scenarios 2 and 3 present better improvement; however, after consultation with experts, the effect of plant staff on resiliency seems to be overestimated in these scenarios. Therefore, scenario 5 can be considered as the best alternative.

SUMMARY AND CONCLUSION

In this study, a framework is proposed to quantify the resiliency of WWTPs as key urban infrastructures in coastal areas. For this purpose, 14 WWTPs in NYC are considered. The WWTPs are characterized based on factors that are used in quantifying resiliency. These factors are weighted using experts' opinions and the AHP method. Actual values of factors are also obtained from different resources. To utilize actual values and weights of factors for quantifying resiliency, a model is developed in MATLAB software based on the MCDM method. The factors are ranked and resiliency is quantified based on the four terms of robustness, rapidity, resourcefulness, and redundancy.

WWTPs are compared considering the obtained values for resiliency. Based on the results, the most effective factors are determined. An uncertainty based method

Table 7 | Scenarios proposed for resiliency improvement of Rockaway WWTP

Scenario no.	Description	Previous value of resiliency	Improved resiliency	Percent of increase in resiliency	Cost of each scenario (m $)
1	30% increase in Ra_3, Rs_1, Ro_4^a and building dewatering facilities (Rs_2)	43.42	46.87	7.94	144.278[a]
2	100% increase in Rs_1		45.76	5.38	1.763
3	100% increase in Rs_1 and building dewatering facilities (Rs_2)		47.61	9.64	8.763
4	30% increase in Ro_4		44.88	3.36	1.750
5	30% increase in Ro_4 and building dewatering facilities(Rs_2)		45.73	5.32	8.750
6	30% increase in Ra_3, Rs_1, Ro_4 and Rd_3		45.03	3.70	137.351
7	30% increase in $Ra_3 + Rs_1 + Ro_4 + Rd_3 +$ building dewatering facilities		46.88	7.95	144.351

[a] $0.3 \times 45 \times 10 + 0.3 \times 41 \times 0.043 + 1.750 + 7 = 144.278$.

is used to determine the range of variability of factors with random elements and to see how these factors could be strengthened to improve resiliency. An example demonstrates how financial resources could be allocated to strengthen the factors attributed to resiliency. Different scenarios are defined to present alternatives for investment to improve resiliency. The cost of implementing the proposed scenarios and the percent of increase in the resiliency is then calculated, and the best scenarios are identified.

Results show that, based on the proposed algorithm for WWTPs, rapidity (Ra) has the maximum effect on resiliency in comparison to the other resiliency terms (i.e., Re, Ro, and Rs). Investigating uncertain factors shows that resiliency has the potential to be improved by variation of some factors. Analysis of the results also shows that investment in non-structural measures is substantially more cost-effective than in structural measures such as expanding the plant capacity. An increase in the number of plant staff could also affect post-stress recovery (Ra_4). The plant staff could accelerate the system's recovery by working before, during, and after a hurricane. The results have demonstrated how partitioning resiliency into several criteria with different sub-criteria, determining the values of those sub-criteria and assigning weights to them, as well as incorporating uncertainties in the flood resiliency analysis, can assist in providing an initial assessment of the required capital investment for a system's preparedness to face flood hazard and disaster.

The proposed methodology is based on a value–weight linear relationship. This simplified assumption made quantification of resiliency easy and possible based on the available data and information. However, complex parametric methods can be proposed and applied for resiliency assessment. For this purpose, studies should be performed on the possible relations between different components (values and weights of different factors) of the method. As for uncertainty analysis, a larger group of respondents may be needed to develop probability distribution functions on the weights of factors and to incorporate this uncertainty into the analysis. Moreover, optimization algorithms can be formulated to determine how a certain amount of budget can be allocated to improve resiliency.

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