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Network Analysis and Characterization of Vulnerability in Flood Control Infrastructure for System-level Risk Reduction

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ABSTRACT

The number of catastrophic events such as extreme rainfalls and hurricanes has been growing. These events pose a major threat to the life safety and economic prosperity of urban regions. Flood control networks play a pivotal role in mitigating the risk associated with the stormwater generated by extreme rainfalls and hurricanes. The objective of this study is to propose a framework to examine the vulnerability in flood control infrastructure networks. This framework applies graph theory concepts and tools to define a vulnerability index for flood control network components (e.g., channels and rivers). The topological attributes of flood control networks are used to determine the vulnerability index based on structural attributes of flood control networks. First, a flood control network is modeled as a directed graph and storage facilities are incorporated into the network. Second, co-location exposure, upstream channel susceptibility, and discharge redundancy are characterized as important vulnerability attributes of a channel in flood control network. Then, these three characteristics are formulized based on the topological attributes of the network and characteristics of channels. The vulnerability index is then determined based on the three vulnerability characteristics. The proposed vulnerability index can be used to evaluate the impact of different risk reduction policies on flood control network vulnerability and determine the optimal mitigation strategies aiming at flood risk reduction, such as widening vulnerable channels, placement of storage facilities in the network or increasing the redundancy of the network. The framework is implemented on two watersheds in Harris County (Texas, USA) and the results' implications for decision-making in infrastructure management and hazard mitigation planning are discussed. The results highlight the capability of the proposed graph-based framework to inform flood risk reduction through evaluation of the vulnerability of infrastructure networks.

1. INTRODUCTION

Floods have caused a significant proportion of disaster-related economic and human losses [1] and pose a significant risk to urban infrastructure and community well-being in flood-prone regions [2,3]. It is projected that flood risk is intensified due to climate change-induced extreme weather events in the future [4–8]. In addition, rapid urbanization exacerbates flood risk by increasing the proportion of impermeable surfaces, which leads to higher peak and volume of runoff following an extreme rainfall [9–11]. Flood control infrastructure networks play a pivotal function in coping with flood risk in urban areas [12]. Hence. proper functioning of flood control networks can substantially reduce flood risk and impacts [13]. Flood control infrastructure includes different components such as dams and levees, reservoirs and basins, pumps and flood gates, and channel network. Flood control networks also include rivers, bayous, and ditches (all referred to as channels in this paper) whose function is draining stormwater runoff. The standard way of assessing the urban flood risk is using Hydraulic and Hydrologic models (H&H models) [14,15]. These models enable estimating the volume of runoff generated by different scenario rainfalls (such as 100-year and 500-year floods) and simulating the flood inundation in nearby neighborhoods [16,17]. However, H&H models have two major limitations in terms of informing about the vulnerability of flood control networks. First, components of a flood control network have different levels of vulnerability to disruption during a flooding event. To account for interdependencies in flood control infrastructure, prioritization of flood risk reduction investments would require analysis of the topology of flood control networks to identify the most vulnerable components. Second, hydrodynamic models allow the representation of the flooded depth and the extent of the flooding areas. However, the translation of such outputs for flood control infrastructure vulnerability assessment is rather limited. For example, the spatio-topological configuration of the channel network as a system property can significantly affect flood control performance. The existing H&H models, however, provide limited insights in performing system-level flood control network vulnerability assessment and identifying the vulnerable infrastructure components for prioritization of risk reduction investments. To address this gap, this paper proposes a new graph-based methodology for vulnerability assessment of flood control networks. Through the use of the graph-based methodology, a channel vulnerability index is defined as a combination of three influencing characteristics: (1) co-location exposure, (2) upstream channel susceptibility, and (3) discharge redundancy. Each attribute is determined using graph-based network measures. Accordingly, the output of the proposed methodology identifies vulnerable channels for flood control infrastructure enhancement to inform hazard mitigation and resilience management plans for flood risk reduction prioritization.

The remainder of the paper is organized as follows. Section 2 provides a literature review on related flood control network vulnerability analysis. Section 3 introduces the conceptualization of flood control network vulnerability and describes the modeling approach for assessment of the vulnerability of channels using graph theory. Section 4 illustrates the application of the proposed framework in two watersheds located in Harris County (Texas, USA) and discusses the implications of the results for policy-making in flood risk reduction. Section 5 summarizes the conclusions and contribution of the study and discusses the limitations and future research directions.

2. LITERATURE REVIEW

Flood risk reduction strategies are categorized into four main groups including *resistance*, *avoidance*, *acceptance*, and *awareness* strategies [18]. Conventionally, urban areas rely on *resistance* strategies in which protective structures such as levees and dams are built to limit the inundation of downstream regions. However, recent trends show that solely relying on *resistance* strategies is not effective for flood risk mitigation [19]. It is generally argued that using a diverse set of strategies increases the redundancy of the flood mitigation portfolios and leads to optimal risk reduction [20]. In this regard, researchers and practitioners advocate the effectiveness of *avoidance* strategies in which the objective is to remove development or steer it away from the most vulnerable areas and *acceptance* strategies, which allow flooding in specific areas or under certain conditions to protect the other areas and provide a relief valve when the volume of stormwater runoff is extensive [18]. Awareness strategies also focus on enhancing the knowledge among citizens and decision-makers using tools such as social media outlets, education and training programs, and workshops.

Flood control infrastructure networks play a pivotal role in devising and implementing *avoidance* and *acceptance* strategies for flood risk reduction. In flood control networks, improving the performance of the channel network by increasing the discharge capacity of channels is a standard *avoidance* strategy for flood risk reduction [21]. Moreover, flood *acceptance* is often achieved through the construction of storage facilities or dedicating open spaces for stormwater retention [22]. Therefore, proper management of flood control networks can be achieved by focusing on both performance improvement of channel network and development and maintenance of storage facilities that absorb the excessive stormwater, which consequently reduces flood risks at the urban scale.

Performance of flood control networks is a function of the characteristics of different infrastructure components such as reservoirs, dams, channels, and floodgates [23,24], as well as interdependencies between the functionality of these different components [25–28]. Hence, vulnerability assessment of flood control networks would require identifying the components that need to be prioritized to enhance the performance of the network from a system perspective. For example, prioritizing channels for enhancement or constructing new storage facilities should not be done based on the impact of the enhancement project on the component itself, it should rather consider the changes of vulnerability in other interdependent components of the system. The standard flood risk assessment is often conducted using H&H models [16,29]. In these models, flow rates are estimated based on employing rainfall-runoff and streamflow projecting models [15,30], as well as soil properties and topological structure of the flood control network [31]. However, H&H models provide limited insights from an infrastructure risk management and vulnerability assessment perspective. First, H&H models do not capture the interdependencies in the flood control network [26]. Interdependence is a system-level phenomenon in which the extent to which a component is vulnerable due to the potential negative impacts of other interconnected components is characterized. Second, flood control networks have complex network configurations in which the network attributes such as topology of the network is a determinant of the system vulnerability [32,33]. Hence, network attributes of flood control infrastructure should be considered in the assessment of vulnerability. Third, although H&H models can identify the high flood risk regions, the resultant flood risk maps provide limited insights for infrastructure vulnerability reduction. These flood maps often cannot inform the infrastructure network vulnerability reduction decisions and help to devise proper strategies to reduce vulnerability from a system perspective. Infrastructure network vulnerability reduction requires identification of the most susceptible channel components and also ones that contribute to the vulnerability of the system as a whole [34]. Thus, there is a need for system-level vulnerability assessment in the flood control network [26] to complement standard H&H models for infrastructure prioritization towards flood risk reduction at the urban scale.

Modeling infrastructure network as a graph where individual infrastructure components are represented as links or nodes has been shown as a powerful tool to analyze system attributes and interdependencies affecting vulnerability [35]. Network analysis has been successfully applied to analyze vulnerability in various infrastructures such as water, wastewater, road, and drainage networks [36–39]. A limited number of studies have employed network analysis to examine flood control networks. For example, in the context of artificial drainage networks, using network properties such as between-centrality, network analysis has been used to identify sub-networks that can be independently managed [40]. In another example, the application of network analysis has been shown for finding the optimal location of sensors that are used to manage and control hydrologic infrastructures located on a flood control network. In this regard, network properties are used to find the combination of sensors with maximum network coverage [41]. Network theory and optimization would also help to select the location and size of retention basins in a watershed, which results in the most cost-effective basin configuration that is also capable of controlling flood optimally [42]. For pump operation management in retention basins and evaluating the effect of capacity expansion on the resilience of the drainage network, the analysis of network topology has been shown to be informative [43].

In another stream of research, several studies have focused on the application of network analysis for assessment of vulnerability in the natural and artificial waterway systems. For example, network analysis has been used for vulnerability assessment of deltaic systems [32], where different topological attributes of the network have been employed to measure the complex and dynamic characteristics of delta networks such as structural overlapping and entropy-based complexity [44]. Also, based on the analysis of topological attributes in a network of channels, Ogie et al. [45] developed a methodology to quantify the vulnerability of hydrological infrastructures such as pump stations and floodgates that are located in a network of waterways [45,46]. Probabilistic network models such as Bayesian network analysis has also been applied for the flood vulnerability assessment. In the methodology developed by Wu et al. [47], a Bayesian network analysis approach was used to model temporal flow rates [47].

The review of the literature shows that network analysis can provide valuable insights for the assessment of vulnerability in interconnected infrastructure that consists of a network of components (such as channels and waterways). Despite the growing use of network analysis for examining infrastructure systems and their interdependencies, vulnerability, and resilience, the existing literature lacks a graph-based methodology and relevant measures for analyzing vulnerability in flood control networks to inform infrastructure prioritization for urban-scale flood risk reduction. Due to the specific characteristics of flood control networks (e.g., the need for consideration of flow and relationship between upstream and downstream components), the existing graph-based methodologies (mainly based on percolation theory) cannot be used for vulnerability assessment of flood control infrastructure. Hence, there is a need for a graph-based methodology that can capture the characteristics of flood control infrastructure and help to identify the components contributing to the vulnerability of the systems. To address this methodological gap, this paper presents a new graph-based methodology to assess flood control network vulnerability. In the proposed methodology, the vulnerability of channels in flood control networks is characterized based on the susceptibility and exposure levels from the upstream channels and upstream storage facilities, as well as the redundancy of the channel to discharge the stormwater runoff. Three network-based measures are devised and examined to capture and represent the vulnerability of each channel in the network. The resulting vulnerability index can be used for characterizing the spatial distribution of highly vulnerable channels to inform flood risk reduction and infrastructure improvement programs. Besides, the results of the proposed methodology would identify regions that are hotspots of vulnerability and could be a candidate for the construction of storage facilities in immediate downstream based on consideration of land availability [41]. Accordingly, the proposed graph-based methodology and measures can complement the existing H&H models for assessment of the risk of flooding in urban areas.

3. METHODOLOGY

3.1. Vulnerability in Flood Control Networks

Different definitions and measures have been proposed for assessing vulnerability in infrastructure systems [48–51]. According to Balica et al. [52], in case of flooding, the vulnerability of the system is the encapsulation of its susceptibility to hazard disruption along with its capability to cope with, recover, and/or adapt to the hazard. Vulnerability of a system component, in this definition, should capture three essential attributes: (1) *exposure:* the extent to which a component is exposed to hazard (such as intense flow rate); (2) *susceptibility:* the extent to which a component is susceptible to failure, disruption, or other predefined adverse condition (such as overflow); and (3) *redundancy:* to what extent a component has buffer (such as local retention) to avoid failure.

In case of flood control network vulnerability assessment, the inherent characteristics of each channel (component), as well as the spatio-topological properties of the network need to be examined. This study considers the discharge capacity as the most significant inherent characteristic of channels in the assessment of vulnerability. The analysis of vulnerability also considers three attributes of channels that are derived from the position of the channel in the network topology. A combination of these three attributes along with the discharge capacity can be used for characterizing the vulnerability of a channel. In this context, the exposure and susceptibility of channels are attributed to the volume of stormwater in the upstream of the channel. However, there are three inherently different sources of hazard-causing exposure and susceptibility for a channel as explained below.

Susceptibility: Stormwater runoff in the channels in the upstream of a channel pose a risk to the downstream channel. The stormwater runoff from the upstream can potentially cause an overflow in the downstream channel and surrounding neighborhoods [32,44]. The greater the volume of stormwater in the upstream channels, the greater the exposure to the flood risk in the channel. In addition, the higher relative capacity of a downstream channel compared to channels in upstream means that the channel is less susceptible to the increased flow in the upstream channels.

Exposure: Stormwater runoff stored in storage facilities (such as retention basins or reservoirs) in the upstream of a channel exposes the channel to a significant surcharge of stormwater if the generated stormwater runoff exceeds the capacity of the facility. In other words, the channel is also at risk of overflow in case of an exceedance of stormwater runoff from the capacity of storage facilities in the upstream. Hence, exposure is a function of proximity to the storage facility in the upstream and the risk of overflow in the facility. The risk of overflow is also a function of the volume of stormwater that the storage facility is designed to absorb (i.e., stormwater runoff in the upstream of the facility), as well as the capacity of the storage facility to store stormwater runoff.

While exposure and susceptibility increase the vulnerability, there is another attribute (i.e., redundancy) that reduces the vulnerability of a channel. Redundancy is a positive attribute of a component or a system capturing the extent of buffer in case of a disruption. For the case of the flood control network, redundancy is characterized as follows:

Redundancy: Redundancy refers to the ability of a channel to properly discharge the stormwater runoff flow to the downstream [24]. The redundancy is a function of (1) the number of alternative paths that the channel relies on to discharge the runoff and (2) the possibility of blockage in stormwater discharge (If a channel is close to a sink node such as a storage facility or an outlet, the channel is subject to less flood risk due to the blockage in the downstream channels). In other words, building a storage facility in the downstream increases the redundancy of channels in the upstream by absorbing the risk of blockage in the downstream channels.

3.2. Modeling Flood Control Network using Graph Theory

In modeling the flood control network as a directed graph, each elements of vulnerability can be formulated based on the definitions provided in the previous section and utilizing channel characteristics and network topology. A flood control network consists of a set of spatially connected channels that drain stormwater runoff generated by extreme rainfalls to the outlet(s) (which are either naturally existed or artificially built to prevent inundation and overflow in the neighborhoods). Considering each channel as an edge, a flood control network can be modeled as a graph $G = (V, E)$, in which channels are the links $E \subseteq \{e_{ij} | e_{ij} \in V^2\}$, and nodes $V = \{v_1, v_2, \ldots, v_n\}$ are the joints connecting the channels or storage facilities. In addition, there is generally no loop in gravity-based flood control systems. Hence, a flood control network can be modeled as a Directed Acyclic Graph (DAG). Figure 1 shows a schematic representation of the DAG model of a flood control network. In the DAG model, edges are the channels and the discharge capacity of edges can be attributed to the weight of edges. For example, in Figure 1, where channel weights are shown on the channels, the discharge capacity of channel *bc* (0.2) is twice more than the discharge capacity of channel *ab* (0.1). Nodes in the DAG model of channel networks can have different attributes. For example, nodes can represent transition points where channel capacities changes, channel intersections, basins, or outlets. In the DAG model of the flood control network, edges have different attributes such as length and flow capacity that can be used to characterize vulnerability. Flow capacity is the maximum rate of discharge that a channel can provide.

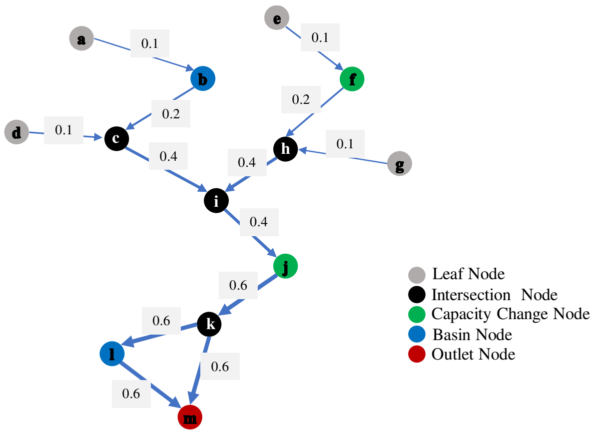

Figure1. Modeling a network of channels as a Directed Acyclic Graph (DAG) consist of channels with different capacities and different types of nodes

For calculation of vulnerability attributes, we applied topological ordering in the DAG model of channels. For graph $G = (V, E)$, an ordered list of nodes $\Omega = \{v_1, v_2, \dots, v_n\}$ is called a topological ordering if for all edges $v_i v_j \in \Omega$, then $i < j$. Algorithm 1 can be used to perform topological ordering in a DAG and generate a sorted listed of nodes in a graph [53]. A sorted list of a directed graph can ease determining the set of channels and storage facilities in the upstream and downstream of a channel and facilitates the calculation of attributes that are defined to characterize vulnerability in flood control networks in this study. In the following sub-section, we formulate the vulnerability attributes described in Section 3.1, and then, combine these three attributes to devise a channel vulnerability index.

Algorithm 1. Topological Sorting of Graph G

```
Procedure Topological Sort
  Input: G(V,E) #G is a directed graph, and d is the ordered set of node indexes of G
set all nodes to be unindexed
for i = 1,...,n
  select any unindexed node v that all its parents are unindexed
  d(v) ← i
  Mark v
Return: (d)
```

3.3. Formulization of Channel Vulnerability in Flood Control Network

3.3.1. Co-location Exposure

Overflow risk exposure in co-located storage facilities in the upstream can contribute to a channel's vulnerability [54]. In this framework, we consider the overflow risk of a storage facility based on the ratio of the stormwater volume in its upstream to its storage capacity as follows:

$$\Gamma_b = \frac{Exposure_b}{Cap_b} \tag{1}$$

Where Γ_b represents overflow risk of a storage facility b, $Exposure_b$ is the volume of stormwater that can be stored in the channels in the upstream of facility b, and Cap_b is the capacity of facility b. The lower the ratio, the more capable the facility to absorb the upstream stormwater and prevent overflow in the downstream channels. From a flood control perspective, storage facilities such as retention basins can be designed and constructed to reduce the risk of overflow in the downstream by collecting the runoff generated in the upstream. In case the runoff inflow exceeds the design capacity of the facility, the downstream channels are exposed to risk of excessive flow that could cause overflow. Therefore, to characterize the exposure for a channel, we need to know (1) the storage facilities in its upstream and the distance between them, which impacts the exposure risk, and (2) the exposure risk of the facilities that contributes to the vulnerability of the channel. Considering these two factors, we designed Algorithm 2 for quantifying the co-location exposure risk of each channel.

Algorithm 2 presents the procedure for calculating Co-Location Exposure (CLE) in each channel. The procedure can be divided into three steps. First, the overflow exposure for each storage facility is calculated (sub-algorithm 2.1) by summing up the storage capacity of all the upstream channels, which for each channel is the volume of stormwater that can be stored in the channel. For example, in the channel network in Figure 1, exposure for storage facility b is equal to the storage capacity of channel ab that equals the length of channel ab multiplied by the area of the channel cross-section. For storage facility *l*, all the channels in its upstream contribute to the exposure of the facility, which include all channels in the network except channel *ab* and channels *km* and *lm*. Then, for each channel, the storage facilities located in the upstream of the channel are identified (sub-algorithm 2.2). Finally, the CLE of a channel is calculated given the overflow exposure of its upstream storage facilities and the distance between the channel and the storage facility ($dis_{i,b}$), by summing over all upstream facilities (sub-algorithm 2.3). for example, in Figure 1, both facilities *b* and *l* contribute to the CLE of channel *lm*, while only facility *b* is considered for calculation of C=the CLE of channel *ci*, and there is no facility contributing to the CLE of channels in the upstream of node *h*. It should be noted that for the calculation of overflow risk for a facility, only the channels that are located between the facility and facilities in the upstream are calculated. The assumption is that each storage facility absorbs the stormwater runoff for all channels in its upstream, and therefore, no risk exposure would be transferred to the other storage facilities in downstream. However, it should be noted that this assumption does not consider cases that multiple storage facilities may fail concurrently and overflow in the upstream facility can impact the facility in downstream. Integration of concurrent failure risk should be addressed in the future research.

Algorithm 2. CLE Calculation for Graph χ

Procedure: CLE Calculation
Input: $\chi(V, E, l, A), B \subset V$, d *# B includes storage facilities, and d is topological-sorted of χ, l includes lengths of channels, and A includes areas of cross-section of channels*
 # sub-algorithm 2.1: calculating exposure of each facility
for b in d
  if b is in B
    $Upstream\ (b) = []$ *#Upstream includes all channels in the upstream of channel b*
    $Upstream\ (b) \leftarrow$ all edges in upstream $\subset E$
    $Exposure\ (b) \leftarrow$sum over $A \times l\ for$ edges in $Upstream\ (b)$
    remove $Upstream\ (b)$ from E
 # sub-algorithm 2.2: assign storage facilities of each channel
for i in E
  $SF(i) \leftarrow$ storage facilities in upstream of i *#SF contains storage facilities in upstream of the channel*
 # sub-algorithm 2.3: calculate CLE for each channel
for i in E
  for b in $SF(i)$
    $dis_{i,b} \leftarrow$ node distance between i and b *#$dis_{i,b}$ is the topological distance between channel and the storage facility*
    $CLE\ (i) += \frac{1}{dis_{i,b}} \times (1 + \frac{\text{Exposure (b)}}{\text{Cap (b)}})$
Return: χ

3.3.2. Upstream Channel Susceptibility

Flow dynamics of flow transport is one of the factors greatly influence the vulnerability of the channels in flood control networks. H&H models quantify flow transport dynamics using the differential equations as well as hydrology and surface characteristic inputs. In this study, we adopted the approach developed by Tejedor et al. (2015) [32] to consider the transport dynamics in graph-based analysis of river and channel networks. To do so, we developed Upstream Channel Susceptibility (UCS) index that examines the extent to which a change in flow of upstream channels can impact the flow of a channel by aggregating impacts that the flow from all its upstream channels inflict on the channel of interest. Algorithm 3 shows the calculation procedure. To calculate the UCS value for each channel, first, a fixed percentage of increase in the flow of the channel is considered (ρ). The influence of upstream channel u on the susceptibility of channel i is denoted by η_{iu}^{ρ}, which shows the ratio of increase in flow of channel u that leads to increase in flow of channel i in the downstream of u by ratio ρ. In this calculation, it is assumed that the flow of channel i is influenced by channels that are in the upstream of channel i but not in the upstream of any storage facility that channel i is exposed to. In fact, the influence of channels in the upstream of any storage facility that channel i is exposed to considered to be absorbed by the facility and the risk of overflow is reflected in the calculation of CLE. For example, in Figure 1, the flow in the channel *ci* is influenced by the changes in the flow of channels *bc* and *dc*, and the influence of channel *ab* is considered in the CLE of the channel that considers the overflow risk of facility *b*.

A high UCS value means that a channel is susceptibility to the increase in flow of channels in the upstream. A high UCS value can be due to: (1) lower capacity of a channel compared to the channels in the upstream and (2) the channel being linked to a large number of channels in the upstream. To reduce the UCS, additional storage facilities can be added in the upstream of the channel to reduce the number of channels in the upstream whose flows lead to the downstream channel. Increasing the downstream channel capacity can also reduce its susceptibility. Thus, the UCS measure also captures the extent to which an increase of discharge capacity in a channel leads to an increase in the vulnerability of other channels in the downstream. Accordingly, the UCS measure informs infrastructure enhancement decisions considering the system-level impacts of the decision rather than focusing on the regional consequence of an enhancement project.

Algorithm 3. UCS Calculation for Graph χ

Procedure: UCS Calculation

Input: $\chi(V, E, l, A), B \subset V$, d , ρ # *B includes storage facilities, and d is topological-sorted of χ, l includes lengths of channels, and A includes areas of cross-section of channels*

```
for e in E
  SF(e) ← storage facilities in upstream of FN(e) # FN(e) is the start node of the channel e
  ψ ← Reversed (d) #reversed of the topological ordered list of nodes in the channel network
  Upstream (e) ← edge in ψ that is in Upstream FN(e) and not in ∪_{j⊂SF(e)}(Upstream (j))
  for u in Upstream (e)
    increased (u) = (1 + ρ) × Capacity (e)
    reduceCap (u) = min (sum(Capacity(adjacents (u)), 0.9 × Capacity(neighbor(u))))
    UCS (e) += (increased (u) − reduceCap (u)) / increased (u)
Return: χ
```

3.3.3. Discharge Redundancy

Discharge Redundancy (DR) of a channel depends on the number of sink nodes that the channel can drain to (i.e., outlets and basins in the downstream). DR captures the redundancy of the channel to discharge stormwater runoff in case of a disruption in the downstream. Any disruption in the downstream of a channel influences the stormwater flow in the channel and can cause runoff propagation into the neighborhood. For example, blockage of channels in the downstream due to sediment or debris accumulation could lead to overflow in upstream channels. Two factors could impact the redundancy of a channel. First, the higher number of paths to sink nodes increases the discharge redundancy since, in case of blockage in a path, an alternative path can discharge the stormwater flows downstream. Second, discharge redundancy is influenced by the distance between a channel and sink nodes. In this regard, any downstream blockage could cause runoff backpropagation. The risk of blockage is associated with the length and size of the channels that connect the channel to the sink node. A longer and larger channel poses higher risk of blockage [4]. DL is calculated by assigning weights to different paths between channels and sink nodes, where path's weights are functions of the distance between the channel and the sink node. Thus, discharge redundancy is calculated by assigning weights to different paths between channels and sink nodes, where a path's weights is a function of the distance between the channel and the sink node. The summation of the weighed paths, then, determines the discharge redundancy of a channel.

Algorithm 4. DR Calculation

Procedure: DR Calculation

Input: $\chi(V, E, l, A), B \subset V$, *# B includes storage facilities, and d is topological-sorted of χ, l includes lengths of channels, and A includes areas of cross-section of channels*

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1  Sink ← χ.outlets, B  #Sink includes the outlet of the channel network (node with outdegree equal zero)
2  for e in E
3    for s in Sink
4      If haspath (χ, TN(e), s) # TN(e) is the end node of the channel e
5        d = |path(TN(e), s)| #d is the topological length of path between the channel and the outlet
6        DR(e) += w(d) # w(d) is the weighted value of d
7  Return: χ
```

3.3.4. Channel Vulnerability Index

The vulnerability of a channel is a function of CLE, UCS, and DR. CLE and UCS would increase the channel vulnerability while DR would reduce its vulnerability. Accordingly, we characterize the channel vulnerability index ζ using Equation (2) [55].

$$\zeta_e = f(CLE_e, UCS_e, DR_e) = \frac{CLE_e \times UCS_e}{DR_e} \quad (2)$$

The channel vulnerability index calculated using Equation (2) evaluates the vulnerability of channels from a system-level perspective considering the structural and topological characteristics of the channel network, as well as characteristics of each channel that impact its ability to discharge stormwater without an occurrence of overflow in the neighborhood of the channel. It should be noted that the proposed approach for vulnerability assessment is based on characteristics of physical infrastructure and does not consider rainfall scenarios. In fact, the vulnerability assessment framework presented here aims at identifying the channels and areas in the network that need to be prioritized for channel improvement or basin construction projects that reduces the risk of inundation in the area regardless of the extent of hazards such as rainfall duration and peak value, as well as distribution of rainfall.

4. FLOOD CONTROL NETWORK VULNERABILITY IN HARRIS COUNTY

The application of the proposed methodology and measures was demonstrated in two major watersheds in Harris County, Texas (USA). Harris County is the third-largest county in the United States and has more than 4,023 km of channels in its flood control network. It comprises 22 watersheds, all of which drains into Galveston Bay. The flood control system in Harris County performs well under normal rainfall. Extreme weather events such as hurricane Harvey, however, can pose a great risk to the county and cause urban flooding. Using the proposed graph-based method and measures, we examined the flood control network vulnerability in two major watersheds in Harris County: Brays bayou and Greens bayou watersheds. Both of these watersheds experienced extensive floods over the past decade including Tax Day Flood (2016), Memorial Day Flood (2016), and Hurricane Harvey (2017). Table 1 shows the characteristics of the studied watersheds.

Table 1. Characteristics of Brays bayou and Greens bayou Watersheds [56]

Characteristic	**Watershed**	
	Brays bayou	**Greens bayou**
Drainage Area (sq. Miles)	127	212
Open Streams (Miles)	12	308
Population (2010 U.S. Census)	717,198	528,720
Primary Streams	Brays bayou Keegans bayou Willow Waterhole bayou	Garners bayou Greens bayou Halls bayou Reinhardt bayou

4.1. Analysis Procedure

To demonstrate the application of the graph-based methodology and measures in the two watersheds in Harris County, we use the procedure presented in Figure 2. First, we collected and processed the GIS data of the flood control networks in the watersheds. Flow capacity of channels as well as location and storage capacity of the storage facilities were estimated. Then, the network of channels was constructed using the GIS data of the network. The network was modified in order to remove errors such as incorrect flow directions, disconnected polylines, and mismatched intersections. Storage facilities were incorporated in the network model, and then, different attributes of vulnerability as well as the vulnerability index were calculated for each channel using the algorithms elaborated in the previous section. Finally, the results were mapped and examined in order to assess the vulnerability of the flood control network in the study area form a system-level perspective, and the implications of results for infrastructure vulnerability reduction were identified.

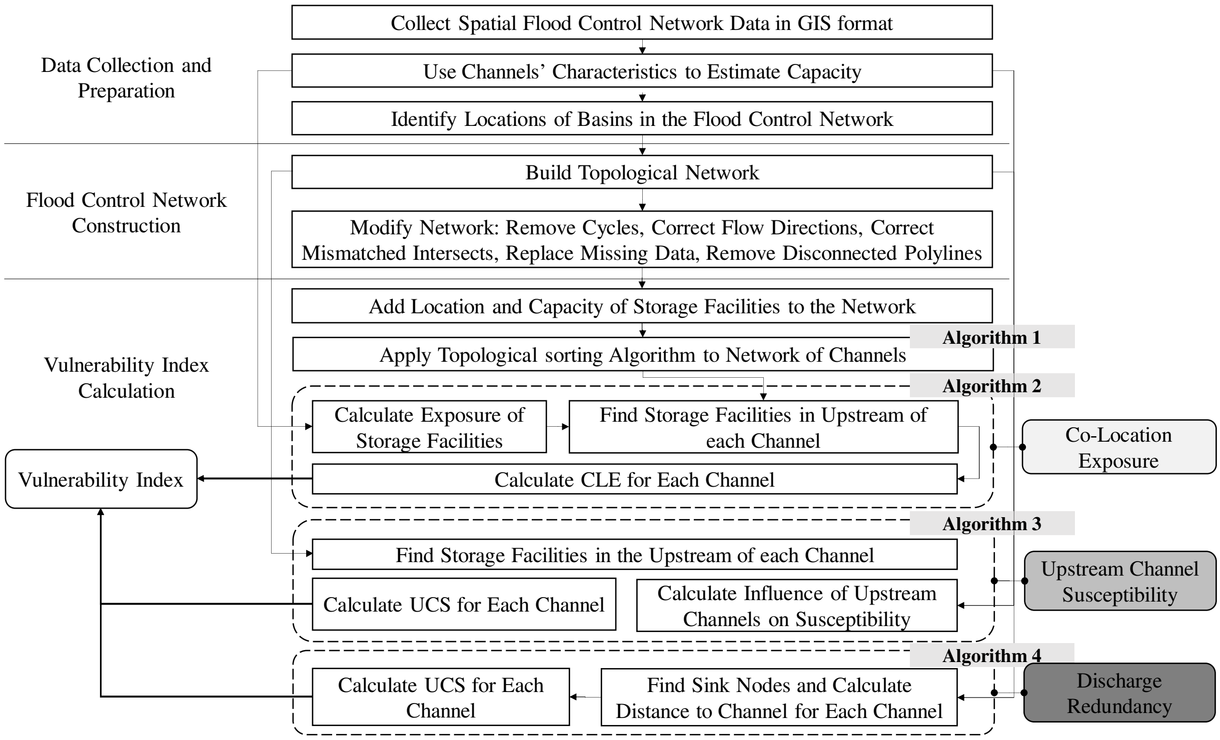


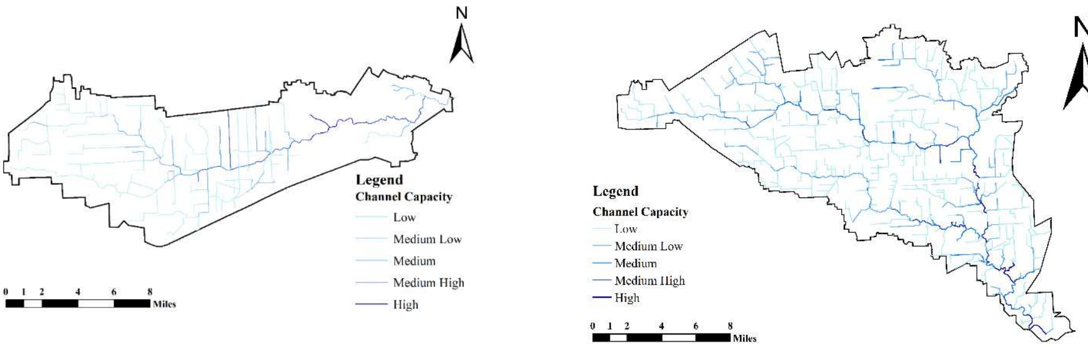
Figure 2. Overview of the Proposed Framework

4.2. Data Collection and Network Modeling

The capacities of channels were estimated using the Manning equation (Equation (3)):

$$(Q_c)_{ij} = \frac{\alpha}{n_{ij}} \times (A_{ij})^{\frac{2}{3}} \times (R_{ij})^{\frac{1}{2}} \times (S_{ij})^{\frac{1}{2}} \tag{3}$$

Where $(Q_c)_{ij}$ is the flow capacity of channel ij, α is a constant, n_{ij} is manning coefficient for channel ij, A_{ij} is the area of cross-section of channel ij, R_{ij} is the hydraulic radius of channel ij, and S_{ij} is the slope of the channel *ij*. For the channels with missing data, the capacity of adjacent channels was used to estimate the discharge capacity. Figure 3 schematically shows the distribution of channel capacities in two watersheds.



(a) *(b)*

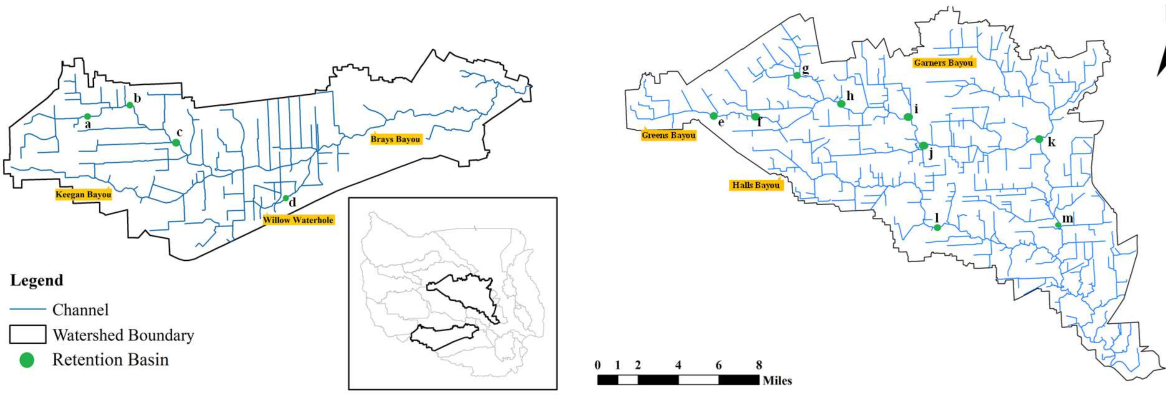
Figure 3. Capacity of Channels in the Flood Control Network

Figure 4 shows the map of the flood control network and the storage facilities in the study area. Flood control network data of the two studied watersheds in Harris County is provided by Harris County Flood Control District (HCFCD) [56], including channel characteristics, the geographic location of each channel, as well as the connection of channels. In addition, the storage facility data were collected through organizational websites and reports. We mapped the information to its closest node in the network [56]. The storage capacity of the facilities was also gathered from the official documents (summarized in Table 2). For the missing data, the capacity was estimated based on the area of the facility. Based on abstracting the flood control network and modeling it as a DAG, there are 224 nodes and 223 edges in Brays bayou watershed and 692 nodes and 691 edges in Greens bayou watershed.

Table 2. Characteristics of Bains in Brays Bayou watershed

Major Retention Basin	**Capacity ($gal \times 10^6$)**
Brays bayou watershed	
Old Westheimer	200
Eldridge	1,500
Willow Waterhole	600
Arthur Story Park	1,100
Greens bayou watershed	
Kuykendahl	757.6
Glen Forest	291.3
Cutten	300*
Halls Park	231
Antoine	538
Lauder	391
Aldine Westfield	407.3
Verde Forest	1,360
Lower Greens bayou	765.4

**estimated (no data available)*



code	Major Basin	code	Major Basin	code	Major Basin
a	Eldridge	f	Antoine	j	Lauder
b	Old Westheimer	g	Glen Forest	k	Verde Forest
c	Arthur Story Park	h	Kuykendahl	l	Halls Park
d	Willow Waterhole	i	Aldine Westfield	m	Lower Greens bayou
e	Cutten				

Figure 4. Study Area and Topology of Flood Control Network

4.3. Flood Control Network Vulnerability Assessment

In this section, the results related to implementing the proposed framework for vulnerability assessment of flood control network in the study area are presented. The three attributes of vulnerability are calculated for all channels in the study area, results are mapped, and discussed. Moreover, the implications of the results for decision-making in infrastructure vulnerability reduction are discussed.

4.3.1. Co-location Exposure Mapping

Figure 5 shows CLE for channels in Brays bayou and Greens bayou watersheds. In Brays bayou watershed, it can be seen that the channels that flow to the bayou have low CLE (box a). The result indicates that the storage facilities are located in this region are capable of absorbing the stormwater runoff in the upstream. In the Waterhole bayou, however, there are channels with medium CLE located in the downstream of the storage facility (box b). It indicates that the facility requires more capacity to absorb the upstream runoff in case of a flood. In addition, in the Central part of Brays bayou and in the downstream of the Aurthr Story Park basin (box c) the CLE is relatively high. Although the basin may be able to properly absorb the low-intensity rainfall, however, the high CLE shows that the downstream of the basin are vulnerable due to the overflow of the basin in case of extreme rainfalls. In the Greens bayou watershed, high CLE can be observed in the downstream, specifically, in the neighborhood of the Lower Green bayou basin (box d). The high value of CLE is due to the high overflow risk from the co-located basin. Also, CLE in the downstream of the basin located in Halls bayou is high, and consequently, the CLE for the channels in the downstream of the intersection of the Garners bayou and Halls bayou is impacted by the co-location effect between the two bayous (box e). This result shows an example of the impact of network topology on the vulnerability of channels.

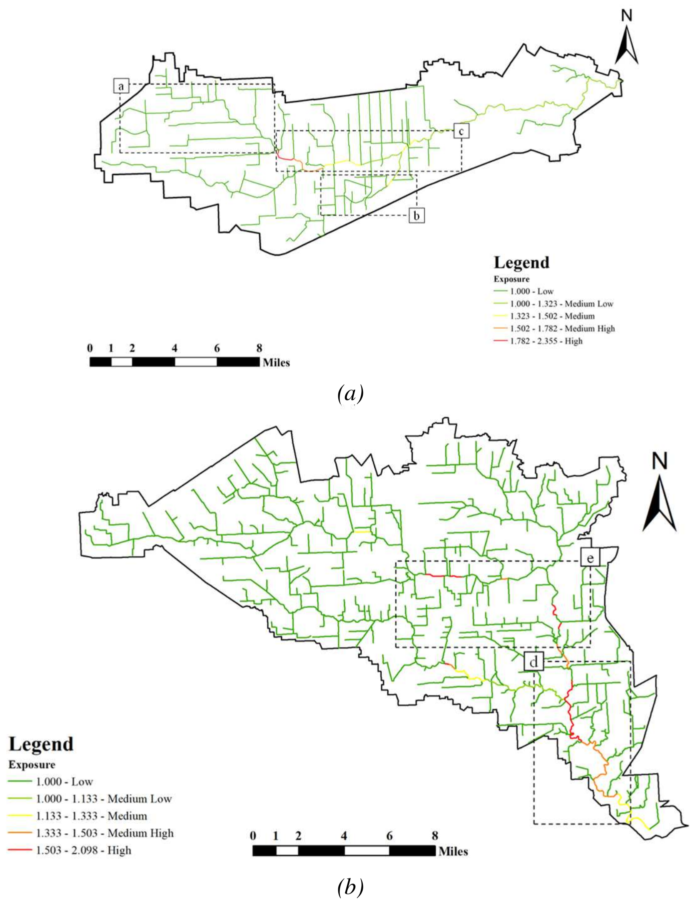
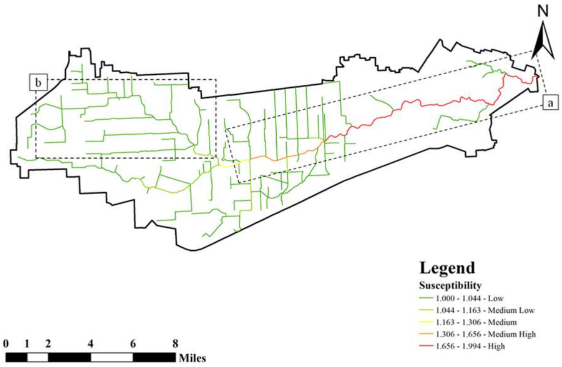


Figure 5. CLE Map for two watersheds' channels; (a) Brays bayou and (b) Greens bayou

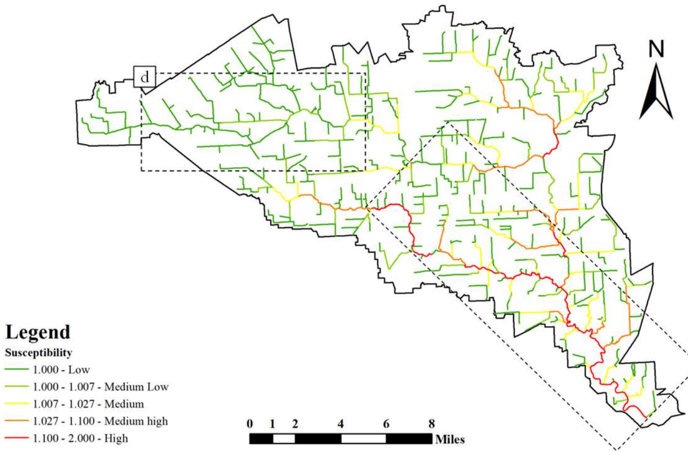
4.3.2. Upstream Channel Susceptibility Mapping

In the next step, we calculated the upstream channel susceptibility (UCS). Figure 6 shows the UCS map of the study area. As shown in Figure 6 (a), the UCS in Brays bayou is significantly higher in the mainstream of Brays bayou (box a) compared to the other channels that flow into the mainstream. This result shows the extent to which the susceptibility of each channel is affected by its position in the network topology. In the case of Brays bayou, the construction of basins would be a proper policy to absorb the impact of upstream channels. However, the space limitation for the construction of large basins often leads to reliance on channel enhancement and widening. Such projects currently form a majority of flood risk reduction projects in Brays bayou watershed [57]. It is also worth noting that the presence of storage facilities, which are responsible for absorbing the influence of upstream channels' susceptibility leads to low UCS in the Northwest of the watershed (box b).

Figure 6 (b) shows the UCS map for the Greens bayou watershed. As opposed to Brays bayou, Greens bayou is formed by smaller sub-network of channels that converge in the downstream of the watershed. Therefore, the distribution of UCS is sparser throughout the watershed. However, the mainstream of Greens bayou and Halls bayou have channels with high UCS (box c). The topology of the sub-network, which has a similar structure as Brays bayou watershed and lack of any storage facility contributes to the high UCS in this mainstream. Also, the Northwest of the watershed (box d) has generally low UCS due to the presence of storage facilities that can control the increase of flow in the upstream channels.



(a)



(b)

Figure 6. UCS Map for two watersheds' channels; (a) Brays bayou and (b) Greens bayou

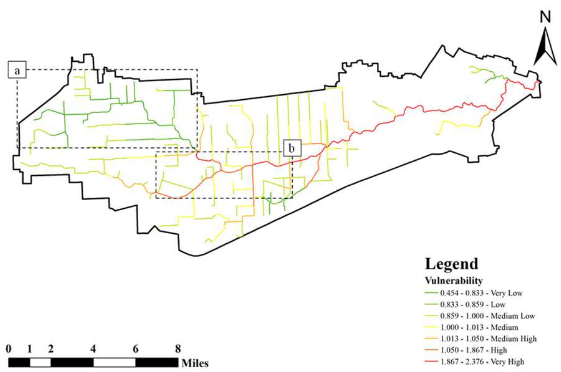
4.3.3. Discharging Redundancy Calculation

Discharge redundancy was also calculated for channels in the network. Channels in the Northwest part of Brays bayou watershed have generally higher DR, however, channels in the upstream of the main branch of Brays bayou have generally less redundancy. This is due to the fact that these channels have high distance from the outlet and there is no alternative sink node in their downstream. In the Greens bayou watershed, considering the impact of storage facilities and the outlet, the DR for a majority of channels in Greens bayou is high, while in the contrary, channels in Halls bayou and Garners bayou have lower redundancy. Generally, the flood control network in Brays bayou and Greens bayou are tree-like; therefore, the number of different paths to sink nodes is one, which reduces the discharge redundancy of channels.

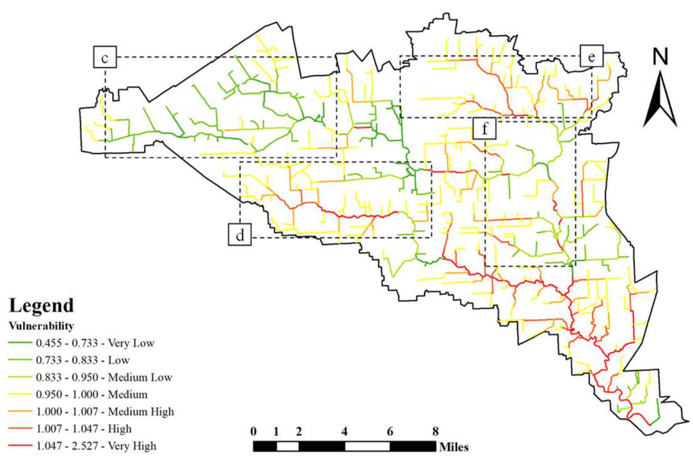
4.3.4. Flood Control Network Vulnerability Index

Combining the impacts of co-location exposure, upstream channel susceptibility, and discharge redundancy, the vulnerability index created in this study can represent the overall vulnerability of channels. Figure 7 shows the channel vulnerability index for Brays bayou and Greens bayou watersheds. The results show that in the Northwest of Brays bayou watershed (box a), the vulnerability index is low, which is due to the presence of well-distributed storage facilities with sufficient capacity to absorb the upstream stormwater runoff (providing discharge redundancy for the channels in the upstream). The channel sections in the mainstream of the Brays bayou are highly vulnerable. In the region close to the intersection of Keegan bayou and Brays bayou (box b), the main cause of the vulnerability is the high distance to sinks and the presence of a basin with high overflow risk in the vicinity. Although these impacts are reduced in the downstream channels, the absence of any storage facility increases UCS. A common approach for vulnerability reduction in such cases would be enhancing channel flow capacity. However, any increase in the flow capacity of channels in the upstream would increase the susceptibility of channels in the downstream. In this case, upstream channels would be able to collect a high volume of stormwater runoff, however, the downstream would not be able to drain the excessive volume of runoff collected by the upstream channels, and therefore, overflow would be expected. Consequently, any enhancement project needs to consider the impact of network topology on the vulnerability in the network instead of focusing on increasing flow capacity in a specific region.

A similar pattern can be seen in the Greens Bayou watershed (Figure 7 (b)). The proper distribution of basins with sufficient storage capacity led to a low vulnerability in the Northwest of the watershed (box c). On the contrary, the lack of storage facilities as well as the configuration of channels in the Southwest part (box d) led to the formation of clusters of vulnerable channels. A similar situation is observed in the Northeast part of the Greens bayou watershed (box e). The presence of Lower Green bayou and Verde Forest basins that are capable of absorbing excessive runoff has reduced the vulnerability in the middle part of the Garners bayou (box f).



(a)



(b)

Figure 7. Vulnerability for Flood Control Channels in (a) Brays bayou, and (b) Greens bayou

4.4. System-level Flood Risk Reduction Implications

System vulnerability results from its intrinsic characteristics and the decisions made by managers and operators. Proper vulnerability assessment should (1) help practitioners and decision makers to better understand the causes and profile of vulnerability in the system and (2) enable evaluating the impacts of different policies on the vulnerability reduction. The proposed framework achieves both criteria by examining vulnerability from a system perspective. For example, we discussed the potential of enhancing channels and construction of storage facilities as a structural solution for vulnerability reduction in the flood control network. However, construction of storage facilities often requires availability of open land, which might not be feasible in metropolitan areas due to limited spaces. Hence, prior to recommending construction of retention basins, we may need to assess limitations for policy implementation. In this paper, we used road density as an indicator of open space availability to assess the feasibility of storage facilities in a watershed. The association between road density and urban expansion [5] proves that road density is a proper structural indicator for land use transition, as a higher density of road network indicates a lower open space availability [58]. To examine the feasibility of retention basin development for reducing upstream susceptibility, we overlaid the vulnerability map of flood control network in Greens bayou watershed with the road density map (aggregated in census tract level), measures in Miles/Sq. Miles unit, as shown in Figure 8. It can be seen that, although the construction of a storage facility can reduce the vulnerability of channels in the downstream of Halls bayou (box a), it is practically infeasible due to the unavailability of open spaces. On the contrary, the channels located in the downstream of the intersection of the Garners bayou and Greens bayou (box b) have low vulnerability, which is due to the presence of storage facilities. The road density map shows that the construction of these facilities was a feasible option in these areas. Similarly, in the Southwest of the watershed, the construction of storage facilities may reduce the vulnerability of channels since the map shows that there should be sufficient open spaces in the region.

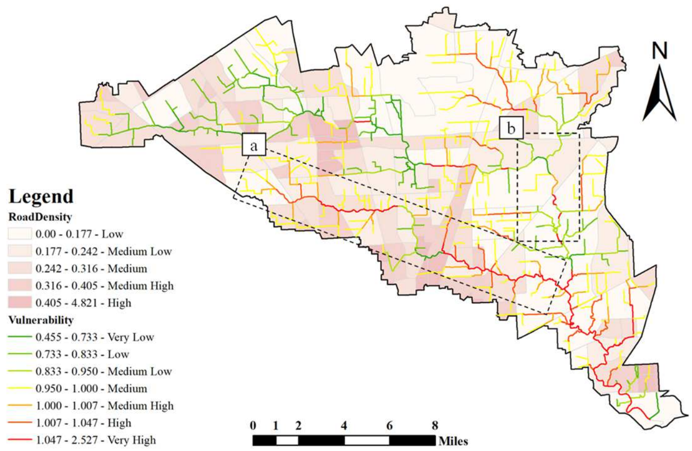


Figure 8. Flood control network vulnerability vs. road density in Greens bayou

5. CONCLUDING REMARKS

This paper presents a graph-based methodology and measures for analyzing and characterizing vulnerability in flood control infrastructure (e.g., channels and rivers). The proposed methodology departs from the existing H&H models for analyzing urban-scale flood risk due to: (1) its focus on flood control systems to inform infrastructure prioritization; (2) its capability to capture structural topology and interdependencies among different channels in assessment of vulnerability; (3) its characterization of vulnerability based on three fundamental attributes: Co-Location Exposure (CLE), Upstream Channel

Susceptibility (UCS), and Discharge Redundancy (DR); (4) its ability to examine system-level effects of risk reduction measures; and (5) its ability to evaluate channel vulnerability without the need for extensive data and computational resources and efforts (as usually required in H&H modeling).

The application of the proposed methodology and measures in two watersheds in Harris County shows the capability of the proposed vulnerability characterization framework and index in identifying the vulnerable channel components. The results of the case study show that, other than the properties of channels and network structure, storage capacity can significantly impact the spatial patterns of vulnerability in the flood control network. For example, the Northwestern region of Greens bayou watershed presents lower vulnerability due to the presence of distributed storage facilities. In the downstream of the Garners bayou, the abundance of open spaces for storage of runoff contributes to the low vulnerability of channels in this region. In densely urbanized areas such as the downstream of Halls bayou where the construction of storage facilities in not feasible, channel enhancement would be a more feasible infrastructural solution. However, the impact of channel capacity increase on downstream channels should be considered.

H&H models provide valuable insight for the determination of inundated areas and assessment of damages. However, from the infrastructure management and hazard mitigation perspective, there is a critical need for identifying the causes of such vulnerabilities in flood control network. In fact, the results of the H&H models enable accurately determining the expected inundation maps and estimating flood damages, which help preventing damages by avoiding further urban developments in areas with higher risk of inundation and preparing emergency response needs for areas with high risk of inundation and damage. However, from flood control infrastructure perspective, practitioners need to have a better understanding regarding why a specific area has risk of inundation and how flood control network can be improved in order to reduce the risk. The proposed framework enables vulnerability assessment and cause identification and helps policy feasibility evaluation for risk reduction (e.g., development prioritization, channels widening, storage facilities placement, storage capacity expansion, and redundancy building). This all attributes to the proposed graph-based vulnerability index that encapsulates the impact of network topology and storage facility on flood control network vulnerability. Hence, the proposed method and measures can provide useful tools for decision-makers to effectively allocation limit resources to infrastructure investments that systemically reduce vulnerability in different watersheds (or systems of watersheds).

The proposed framework and this study present multiple avenues for further development in future research. First, land characteristics such as the proportion of impervious surface, land slope, and development pattern of each channel can be included in determining the overflow risk calculation. This study aimed to assess the vulnerability for channels from a system-level perspective considering topological network properties, and therefore, it does not consider any specific rainfall scenario for the analysis. The outcomes of the H&H models can be integrated with the proposed vulnerability assessment framework to examine the vulnerability in channels given different flooding scenarios (under different rainfall intensities). In addition, a probabilistic scheme for considering flow change in each channel can be included to encapsulate the flow dynamics of the flood control network. Moreover, future research can consider the flow impact from hydrological factors, as well as the risk of overflow. For example, type of the channel (i.e., meandering or straight) can greatly impacts the flow rate [56]. Hence, future research can examine the impact of such factors on the vulnerability quantification. Finally, a system-level vulnerability assessment can provide insight for decision makers to identify vulnerable components that exacerbate the vulnerability of the whole system. However, prioritization of corresponding mitigation actions requires a thorough understanding of the potential impacts (e.g., losses related to population, environmental impacts) of different flood scenarios. Therefore, a combined system-level vulnerability assessment and flood impact analysis will be conducted in our future research to enable the identification of targeted mitigation actions based on their contribution to the reduction of flood impact.

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