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Potentialities of Complex Network Theory Tools for Urban Drainage Networks Analysis

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Key Points:

- Potentialities of complex network theory (CNT) for urban drainage network analysis
- Tailored CNT tools embedding prior information for urban drainage network analysis
- Vulnerability, monitoring design, contaminant and pathogenic spreads analysis of urban drainage networks

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Abstract Urban drainage networks (UDNs) represent important infrastructures to protect and maintain community health and safety. For these reasons, technicians and researcher are focusing more and more on topics related to vulnerability, resilience and monitoring for controlling illicit intrusions, contaminant and pathogenic spread. In the last years the complex network theory (CNT) is attracting attention as a new, useful and structured approach to analyze urban systems. The aim of this work is to evaluate potentialities of CNT approaches for UDNs vulnerability assessment and monitoring system planning. Limits and potentialities of applicability of CNT tools to UDNs are first provided evaluating the performances of standard centrality metrics. Then, it is proposed the use of tailored metrics embedding prior information, as intrinsic relevance of each node and pipe flow direction, which derive from the Horton's hierarchy and geometric data (pipe slope), respectively, without performing hydraulic simulations. The analysis is applied on two schematic literature networks of different complexity and to a real case-study. The results suggest that vulnerability/resilience, monitoring design, contaminant and pathogenic spreads can be effectively analyzed using tailored metrics. Therefore, the proposed approach represents a complementary tool respect the more complex and computationally expensive methodologies and it is particular useful for large complex networks.

Plain Language Summary Urban drainage systems are networked infrastructure strongly conditioned by their topology. Tailored complex network theory approach represents a complementary tool to characterize the urban drainage network (UDN) behavior with respect to vulnerability, monitoring design, contaminant and pathogenic spreads.

1. Introduction

Water supply and urban drainage networks (UDNs) are very important infrastructures, and their efficient operation is crucial in modern and smart cities. UDNs can be sanitary systems, which collect and transport wastewater, or combined systems, which also collect stormwater runoff produced during rain events. They are composed of several interconnected components, whose behavior is largely influenced by spatial limits (e.g., slope) and by their connectivity structure, strictly dependent on the urban road network.

In recent decades, the need to propose new management and analysis strategies for such critical infrastructural systems has appeared increasingly required, particularly looking at the effects of more and more severe climate changes, uncontrolled urbanization and infrastructure aging. Barreto et al. (2010) proposed a combination of multi-objective approach and hydrodynamic drainage models for the design/rehabilitation of sewer pipe networks also focusing on investment and flood damages. Vojinovic et al. (2014) proposed an optimization framework and developed two approaches to carry out the UDN rehabilitation under uncertainties, integrating several objectives and levels of performance and costs. The first approach accounts for uncertainties in the objective function evaluation process, while the second one for uncertainties in the optimization process. The two approaches produce almost the same results and identify robustly optimized solutions in terms of the damage and intervention cost. Yazdi et al. (2017) proposed a comparative study of multi-objective evolutionary algorithms for hydraulic rehabilitation of urban drainage networks. Among the innovative techniques aimed at managing urban drainage networks, Piro et al. (2019) proposed real time control (RTC) and low impact development (LID) techniques, which represent a valid and cost-effective solution. Babovic and Mijic (2019) proposed an adaptation tipping points (ATP) approach to investigate the impacts of future rainfall on urban drainage systems. Their idea was to generate a set of adaptation pathways (system storage and green infrastructure solutions) to add additional capacity to the system linked to an economic assessment that considers the ecosystem services and institutional long-term planning policies. Differently, Ngamalieu-Nengoue et al. (2019) proposed a strategy of rehabilitation for UDNs that combines pipes substitution and storm tanks installation to face with the environmental and climate changes, considering green roof quite inefficient for extreme rainfall events. In order to reduce the calculation time, authors proposed an optimization based on a search space reduction methodology, whose purpose is to decrease the number of decision variables of the problem to solve. Bakhshipour et al. (2021) proposed a multicriteria decision-making platform for UDN sustainable planning, considering (de)centralized strategies, able to manage many decisions, objectives, and indicators for solving a complex optimization problem in a reasonable time by delivering realistic solutions.

Also vulnerability assessment for urban water systems is a very important topic, generally defined to analyze the effects of failures (Zhang et al., 2017). Resilience, instead, is a concept that integrates reliability of the network when subjected to the usual loading and minimization of malfunctions in case of unusual situations. It represents an important objective for the system management because it helps to characterize the ability to reduce the damage caused by unexpected events, such as failure (Mugume et al., 2015), or expected changes, related, for example, to climate change and increasing urbanization (Dong et al., 2017). Many studies adopting different methodologies have been proposed for the evaluation of UDN vulnerability about bad operation following rupture, blockage, pump failure (e.g., Mugume et al., 2015), or critical events (Kleidorfer et al., 2009). Chughtai and Zayed (2008) presented a proactive methodology to assess the vulnerability of sewers using historic data and considering various physical, environmental, and operational influence factors, to identify critical elements due to bad functioning, prioritizing inspections and rehabilitation requirements (Del Giudice et al., 2016). Moderl et al. (2009) developed the VulNetUD method, which is for GIS-based identification of vulnerable sites of UDNs using hydrodynamic simulations undertaken using EPA SWMM.

Another important topic is the system monitoring, both in terms of hydraulic operation and for controlling wastewater quality, which is fundamental to ensure its sustainable management, limiting the potential environmental impacts (Gromaire et al., 2001). Design of wastewater quality monitoring system is important for the identification of illicit intrusions (Banik et al., 2017a, 2017b, Sambito et al., 2020) and for controlling specific contaminants and pathogens to support a relatively novel approach, known as wastewater based epidemiology (WBE), which improves the efficacy of traditional epidemiologic studies (Feng et al., 2018; Gracia-Lor et al., 2017; Gonzalez et al., 2020). This aspect is receiving increasing attention since wastewater monitoring currently represents a useful and cost-effective tool to check the community-level transmission of SARS-CoV-2 (McMahan et al., 2021). More recently, Nourinejad et al. (2021) proposed a methodology based on Tributary Search Algorithm that would place sensors in a number of wastewater manholes to detect genetic remnants of SARS-Cov-2.

However, all these methodologies require a series of innovative numerical analysis and a huge amount of data to define properties of the hydraulic models and to reproduce the processes involved. It appears clear that due to their complex schemes, sometime not completely well-known, and to the lack of data or difficulties in accessing information (e.g., flow, diameters, cost of topological surveys, etc.) often it is not possible to simulate the hydraulic behavior of UDNs. In this contest, complex networks theory (CNT) tools represent an effective solution for the study of these systems. In fact, a CNT based approach can represent a preliminary and complementary tool respect to the hydraulic modeling, useful for analysis, management and design of UDNs. It is applicable in the initial phase of the study, being based only on the topological characteristics of the systems (e.g., topological survey) and does not require the use of hydraulic simulations, which are expensive both in terms of time, calculation and amount of data to produce and implement.

CNT comes from a branch of mathematics known as graph theory. It allows the description of sets of objects with their relations, as well as the study of characteristics and behavior of a wide range of real complex systems representable as networks, which can have different structures (Barabási & Albert, 1999; Erdös & Rényi, 1959; Watts & Strogatz, 1998) and diverse functions, such as the exchange of goods and people (transport network), the exchange of information (internet network), the spread of diseases (epidemiological network), the interpersonal relationships (social network), etc. (Newman, 2010). Furthermore, given a network, the applications can be various, for example, identifying the central elements (nodes or links) and the emergent behavior of the system, the network vulnerability, assessing the evolution of the system in space and time, etc.

Recently several authors started to use CNT metrics to analyze tree-like networks, such as UDNs and river networks (Halverson & Fleming, 2015). For example, Zischg et al. (2017) investigated the historical development of complex network topologies in UDNs using the dual representation of the network, showing that the systems present scale-free network characteristics (Barabási & Albert, 1999) and evolve with consistent patterns over time. Krueger et al. (2017) proposed graphs generated using a dual-mapping technique (Hierarchical Intersection Continuity Negotiation) to represent water distribution networks (WDNs) and sanitary sewer networks to explore structure as well as spatial and temporal evolution of these infrastructure systems. Yang et al. (2017) analyzed the scaling and topology of UDNs and their evolution over decades. Meijer et al. (2018) identified the most critical elements in UDNs with respect to malfunctioning of the system as a whole, using the graph theory focused on the structure of the network rather than on hydraulics. Recently, Ganesan et al. (2020) studied the vulnerability of UDNs using CNT and centrality metrics (harmonic and betweenness) identifying the most important nodes in the network useful for further applications in the field of system monitoring. Reyes-Silva et al. (2020) compared two CNT approaches based on the use of Edge Betweenness Centrality (EBC) and Single Destination Shortest Paths (SDSP), respectively. Results of the first approach suggest that EBC is not a good indicator of wastewater flow quantities, while with an appropriate edge weighting factor, the SDSP to the network's outlet has the potential to be used as an indicator for flow transport. Also, contaminant spread in UDNs can be potentially studied using CNT, as done by Zuluaga et al. (2020) that used the network theory together with differential equations to propose a methodology to model and simulate water quality parameters in a hydrological basin.

Respect the few applications to UDNs, the novelty of the present work is represented by the use of CNT tools to analyze vulnerability/resilience, optimal monitoring design and spread of contaminants in UDNs. The aim of this paper consists in evaluating limits and potentialities of standard and tailored centrality metrics. The original aspect of the present study lays in considering the different role of nodes (e.g., inlet nodes, connection nodes, outfall nodes, etc.) embedding the information about their intrinsic relevance (Simone et al., 2022). The concept of intrinsic relevance was introduced in WDNs analysis by Giustolisi et al. (2020), that proposed a novel tailoring of the centrality metrics considering the information about the intrinsic relevance of each node and developed a strategy based on Relevance-embedding centralities (degree, harmonic, betweenness and edge betweenness). Here, ad hoc tailored metrics are used to consider the intrinsic relevance derived by the Horton's hierarchy and the presence of spatial constraints (e.g., slope) derived from the flow direction in the system. The goal is to apply the relevance-based CNT centrality metrics to the direct graph of the UDN to demonstrate that vulnerability, monitoring design, contaminant and pathogenic spreads in UDNs can be usefully analyzed using CNT tools. The main objective of this work is to propose an approach to analyze networks in a preliminary phase of investigation, that is, when only the topological survey is available. Then, it differs from the classic one being based on the network connectivity structure and not on the hydraulic simulation. It can be used in alternative or in combination with previously proposed methodologies, which are more complex, data demanding and computational expensive tools.

The paper is organized in the following way. Section 2 briefly recalls the main basic concepts of the CNT. With reference to a benchmark network, Section 3 reports UDN analysis through standard centrality metrics, while Section 4 illustrates how vulnerability/resilience, monitoring and spread of contaminant can be analyzed using ad hoc tailored CNT tools. Section 5 present the analysis of a small literature network and of a real medium-sized case-study. Concluding remarks are drawn in Section 6.

2. Complex Network Theory (CNT)

2.1. Basic Concepts

Complex network theory (CNT) allows to analyze many real complex systems resorting to the use of graphs. A graph $G = (N_p, L_k)$ represents, in an efficient way, the network model through a set of nodes, $N_p = \{1, \ldots, n, \ldots, N\}$ that represent the main components of the system (e.g., neurons, crossroads, people, manholes, etc.) connected by a set of links, $L_k = \{1, \ldots, l, \ldots, L\}$, that represent the connections between components (e.g., synapses, roads, relations, pipes, etc.).

Within a graph, a sequence of nodes and links is defined as a path. Each path with l links contains $l + 1$ nodes and the *length* of a path is the number of traversed links along the path. The path with the minimum number of links between nodes (i, j) represents the shortest path between them.

The connectivity of a system is described by its topological adjacency matrix $N \times N$ defined as $\mathbf{A} = (a_{ij})$, that indicates whether pairs of nodes are connected or not in the graph. For a simple graph, the *adjacency matrix* corresponds to a logical matrix where elements are all either 0 or 1 (Banik et al., 2015):

$$a_{ij} = \begin{cases} 1 \text{ if } \{i, j\} \in L \\ 0 \text{ if } \{i, j\} \notin L \end{cases} \tag{1}$$

and for $\forall i \in \{1, \ldots, N\}$ $a_{ii} = 0$ (i.e., no self-loops exist).

Each graph describes the characteristics of the system it represents. An indirect graph (e.g., Internet network) is characterized by links that do not have a direction and for which the relationship between nodes $(i, j) \in G$ is symmetric ($a_{ji} = a_{ij}$). Differently, when this does not happen ($a_{ji} \neq a_{ij}$) the graphs is direct (e.g., river networks). A weighted graph, instead, is a graph that assigns a weight to each link (e.g., costs, lengths or capacities) depending on the considered problem. For undirected graphs, the *adjacency matrix* is symmetric with respect to the main diagonal, while for direct graph it is not necessarily. The *adjacency matrix* of a weighted graph reports the weights of the links between nodes in the cells.

Several network properties can be evaluated using a set of metrics, characterized by different ranges of values, which can be related to specific elements (e.g., importance of nodes) or to the overall structure of the system (e.g., network characteristic).

2.2. CNT Centrality Metrics

CNT allows ranking elements in networks according to their topological importance (Freeman, 1977). The topological importance of each single element, also called centrality, is a function of its interactions. The approach is based on the idea that critical components (nodes and links) stand between others playing the role of intermediary in the interactions or in the communications. Greater is the number of connections and paths in which they contribute, higher is their centrality in the network. Several centrality metrics have been proposed to evaluate the most central elements in different real complex systems with respect to various physical phenomena (Newman, 2010). For urban infrastructure networks, such as WDNs, the use of Degree, Harmonic and Betweenness (Freeman, 1977; Giustolisi et al., 2020) has been proposed so far. The first one allows a local and immediate evaluation of the centrality of the elements based on the concept of connection and is the basis of the study on the classification of complex systems (Giustolisi et al., 2017); the other two allow, instead, a global analysis of the systems based on the concept of the shortest paths, which reflects precisely the system behavior.

Degree Centrality, C_i^D (Freeman, 1977), represents the number of links incident upon a node, and it is expressed as:

$$C_i^D = k_i = \sum_{j=1}^{N} a_{i,j} \quad i = 1, \ldots, N \tag{2}$$

where k_i is the degree of the node i in the network and $a_{\mathrm{i,j}}$ is the coefficient of the adjacency matrix. The most central node is that with the highest number of adjacent nodes.

Harmonic Centrality, $H^C{}_i$ (Rochat, 2009), measures the geodesic distance from a node i to all other nodes j in the network and it is denoted by the sum of the inverse of each distance, expressed as:

$$H_i^C = \sum_{j \neq 1}^{N} \frac{1}{d_{ij}} \tag{3}$$

where d_{ij} is the distance, that is, the number of steps, from node i to node j in the network. It measures the centrality of a node i considering how it is relatively close to all other nodes and it can be regarded as a measure of how long it will take to spread information to all other nodes sequentially.

Betweenness Centrality, $C^B{}_i$ (Freeman, 1977), measures how many times each node is crossed by shortest paths between pair of nodes (s and t), and is expressed as:

$$C_i^B = \sum_{s \neq i \neq t \in G} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{4}$$

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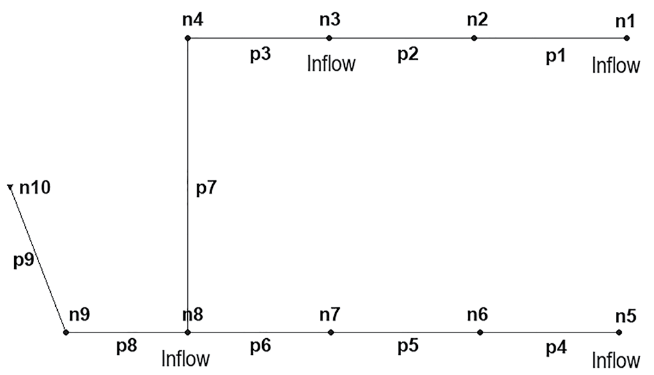

Figure 1. Scheme of the Extran network composed of 10 nodes, $n_n = 10$ (nine manholes and one outfall) and nine pipes, $n_p = 9$.

where σ_{st} are all shortest paths between the pair of nodes s and t and $\sigma_{st}(i)$ are all shortest paths between s and t crossing node i (with i, s, $t = 1, \ldots, N$). The concept of centrality assumes relevance considering that the removal of the most central nodes directly influences "the cost" of the connectivity between other nodes if not the same reachment, in other words it will be necessary to follow longer paths to allow reachability between pairs of nodes.

In terms of links, instead, the Edge Betweenness, C^B_l (Girvan & Newman, 2002), is proposed as metric to evaluate the importance of a link l counting how many times it is crossed by shortest paths between two nodes s and t, expressed as:

$$C_l^B = \sum_{\substack{s \neq t \in G \\ l \in E}} \frac{\sigma_{st}(l)}{\sigma_{st}} \tag{5}$$

where $\sigma_{st}(l)$ are all shortest paths between nodes s and t crossing link l (with s, $t = 1, \ldots, N$ and $l = 1, \ldots, L$).

3. UDN Analysis Using CNT Centrality Metrics

When considering the application of CTN tools to UDNs, it is worth considering that these systems have the following characteristics:

- Spatiality. The system is inserted in the space, and it is characterized by the Euclidean distance and by the slope. It is limited by the impracticability of some connections (e.g., counter-slope) and conditioned by multiple factors (human comportment, climate, politics, etc.).
- Concreteness. The system consists of real and concrete elements (pipe sewers), whose performance is a function of the type of materials, of the age of the system and of their dimension and installation (Giustolisi et al., 2019). For example, pipes with large diameters are more important than pipes with small diameters.
- Unidirectionality. The system generally works by gravity, so that the flow direction is uniquely imposed by the slope. Obviously, the presence of specific devices (such as pumps), allows the flow to head also against the slope.
- Openness. The system generally presents a tree-like structure, without the presence of loops, which instead are recurring in infrastructural networks such as road networks and WDNs. The connectivity structure presents a hierarchical model, where the number of links is equal to n−1 nodes. It represents a minimally connected graph with only one path between each pair of nodes. Consequently, only one shortest path exists between pair of nodes influenced by the flow direction. The metrics based on the concept of shortest paths are computed also considering this aspect.
- Unreachability. The two previous points imply that not all nodes are reachable by the other nodes within the system: for example, all nodes can reach the outfall, but the outfall cannot reach any node.
- Relevance. The system is represented as a set of nodes, and each node has its own intrinsic relevance, which is a function of its role within the system (Simone et al., 2020). For example, storage nodes (reservoirs, tanks, outfalls) represent a sort of hydraulic hubs.

A UDN is a graph where links represent the sewer pipes (n_p) and nodes (n_n) can represent source nodes, connection nodes, storage nodes and outfalls.

In order to evaluate if CNT metrics are effective for UDN studies, dealing with the assessment of vulnerability and resilience, optimal sensor design or spread of contaminant, the schematic Extran network, represented in Figure 1, is used. The use of the Extran network seams trivial, since in this scheme is immediate to individuate the importance of the single elements, but it permits to verify the applicability of CTN metrics, which can be successively used on very complex schemes, not simple to analyze. Table 1 reports the network characteristics.

Figure 2 reports the results obtained by applying the classic centrality metrics to the indirect graph of Extran network. From a hydraulic standpoint, it is known that the outfall (node 10) and the pipes close to it (pipe 8 and

Table 1
Extran Network Characteristics

#Pipe	1st Node	2nd Node	Length (m)	Slope (%)
p1	n1	n2	1,800	0.167
p2	n2	n3	2,075	0.047
p3	n3	n4	5,000	0.565
p4	n5	n6	5,100	0.170
p5	n6	n7	3,500	0.205
p6	n7	n8	5,000	0.189
p7	n4	n8	500	0.181
p8	n8	n9	300	0.183
p9	n9	n10	4,500	0.265

9) are the most important elements. Conversely, following the classic metrics, node n8 exhibits the maximum Degree (Equation 2) and Harmonic (Equation 3) Centrality, meaning that it is the most connected and the most efficient in spreading information. The outfall node results less important because it is the least connected node and it is not close to relevant nodes, although it represents a sort of hydraulic hub.

Figure 3 reports the Betweenness (Equation 4) and the Edge Betweenness (Equation 5) values. The metrics indicate that node n8 and pipe p7 are the most important, being the most traversed by the shortest paths, and fails in assigning null value to the pipe p9 close to the outfall, which is hydraulically relevant. It is important noting that, since there is only one shortest path between each pair of nodes, the denominator of Equations 4 and 5 is always equal to 1.

In conclusion, the centrality metrics Degree, Harmonic, Betweenness and Edge Betweenness are not so adapted to study UDNs. In the following, the use of tailored centrality metrics is proposed and their performances are tested when applied to vulnerability/resilience assessment, monitoring and contaminant spread.

4. Tailored Metrics Embedding Node Relevance and Direction as Prior Information

Various studies proposed strategies to understand the actual role of the topological structure in the operation of real infrastructure systems, assuming all nodes with equal relevance. This assumption for the study of UDNs can lead to a threefold error: all nodes have the same relevance (e.g., a connection node has the same relevance of an outfall), the importance of elements is only based on the connectivity (e.g., large diameters with few connections are less important than small diameters with many connections), and, paradoxically, the outfall has a very low importance, being generally connected to a single pipe (i.e., final pipe of the network), even if it represents a special hub collecting all the wastewater in the network. It follows that to enhance the UDN analysis, the information about the role of nodes in the network must be embedded into CNT tools.

The idea of considering a different intrinsic relevance R_n ($n = 1, \ldots, N$) for the nodes of a system has been first proposed for social networks and WDNs by Giustolisi et al. (2020), with the aim of enhancing the analysis of such systems and to obtain concrete results on the actual role of topological domain features on the emergent behavior of the systems. They defined the intrinsic relevance R_n ($n = 1, \ldots, N$) as an information depending on the type of the network and the analysis to perform and proposed several functions $f\,(R_s, R_t)$ depending on the intrinsic relevance of the ending nodes s and t of each link l. The function $f\,(R_s, R_t) = R_t$, which considers the relevance of the ending node for each link, well identifies the UDN features and has been here considered to customize the standard centrality metrics. Using this function, degree and harmonic are scaled by the relevance R_t.

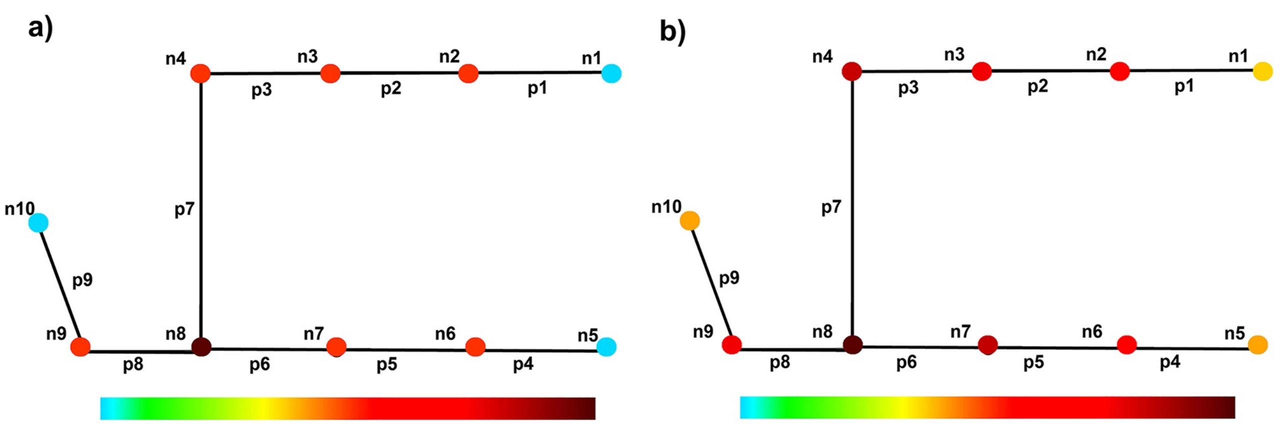

Figure 2. (a) Degree and (b) Harmonic centrality for Extran network.

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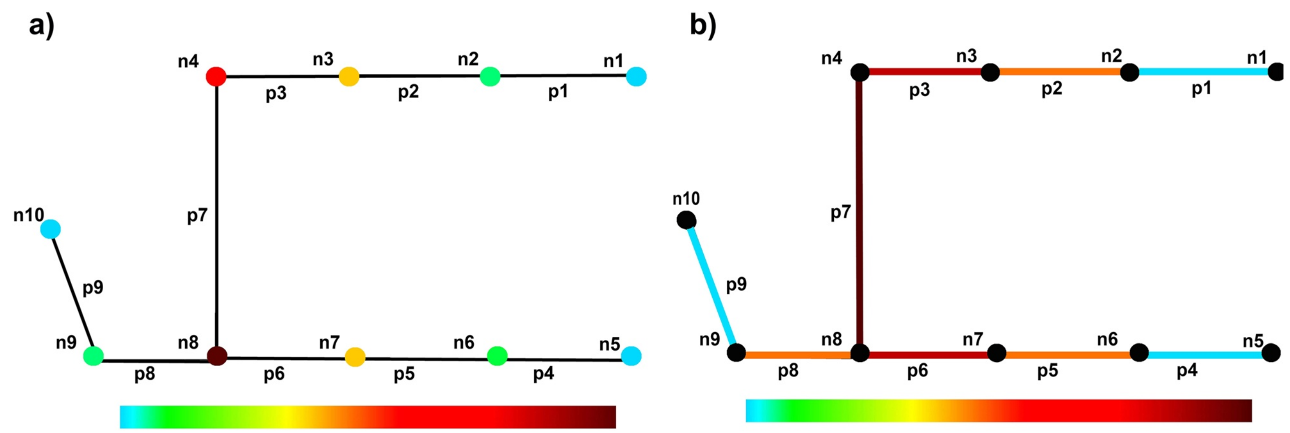

Figure 3. (a) Betweenness and (b) Edge Betweenness centrality for Extran network.

The standard degree, harmonic and betweenness centrality have been tailored embedding the information about the intrinsic relevance of the nodes through the function $f(R_s, R_t) = R_t$ as follows:

$$C_i^D = k_i = \sum_{j=1}^{N} a_{i,j} R_i \quad i = 1, \ldots, N \tag{6a}$$

$$H_i^C = \sum_{j=1}^{N} R_i \frac{1}{d_{ij}} \tag{6b}$$

$$C_i^B = \sum_{s \neq i \neq t \in G} R_i \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{6c}$$

$$C_l^B = \sum_{\substack{s \neq t \in G \\ l \in E}} R_i \frac{\sigma_{st}(l)}{\sigma_{st}} \tag{6d}$$

To preserve the purely topological nature of the strategy, the intrinsic relevance of each node is achieved from the Horton's hierarchy of the system (Horton, 1945). For strategy purposes, it is assumed that pipes converge in nodes and not in pipes. Horton's criterion (Figure 4) states that every elementary pipe (without affluent) is of the first order. It follows that each header node assumes relevance equal to 1. At the confluence of two pipes of the first order, a pipe of the second order is generated, and therefore a node with relevance two. The process continues until the count has considered all the elements of the system. The main pipes (nodes) of the system have the highest order number, equal to 3 in Figure 4. It is important noting that two pipes of different order converge in a pipe that has order equal to the greater between the two confluent pipes. Moreover, the succession of two or more pipes, characterized by the same order, constitutes pipes (nodes) of their same order (relevance).

Further information is added to the metrics considering that a UDN generally works by gravity and the flow direction is uniquely determined by the slope. This implies that UDN topology has to be analyzed considering direct networks and metrics have to embed this information. In this regard, two different Degree centrality measures can be used: in-Degree, counting the links that enter a node, and out-Degree, counting the links that leave a node. The Harmonic centrality also changes according to the directions chosen between the pairs of nodes. Particularly, the tailored out-Harmonic considers the information that comes out from a node, while the tailored in-Harmonic considers the information that enters a node. The out-Harmonic centrality indicates how close a node is to those receiving its information, while the in-Harmonic centrality indicates how close a node is to those from which receives the information. In the following analysis the in-Degree and the out-Harmonic metrics are used.

On the other hand, in a direct network, the calculation of the Betweenness is based only on the number of oriented shortest paths between each pair of nodes. Obviously, pipes hosting devices can also work against the slope (e.g., pumps).

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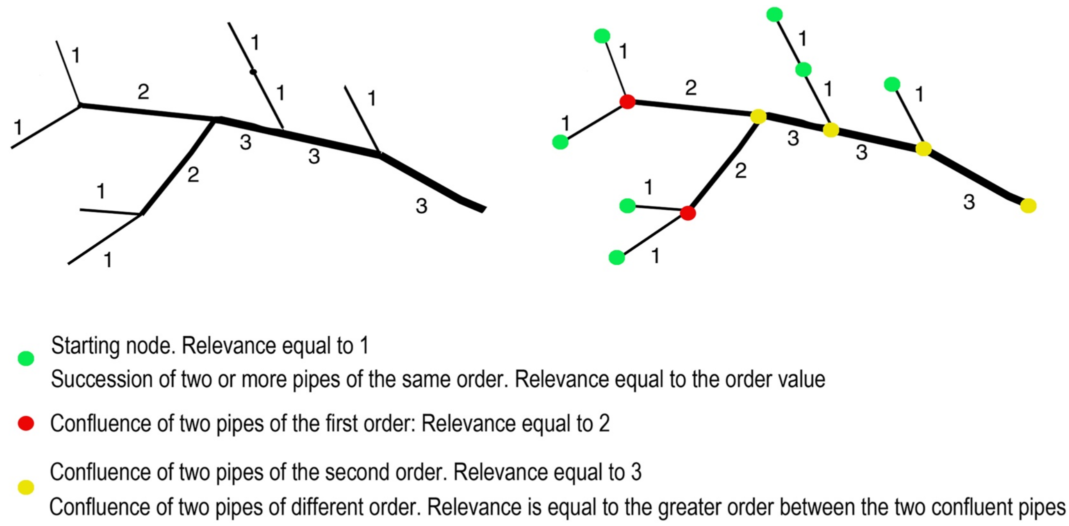

Figure 4. Horton's streams hierarchy.

4.1. UDN Analysis Using Tailored Centrality Metrics

In this paragraph the tailored metrics are applied to understand if they can draw useful information on the system, in particular on vulnerability/resilience, optimal sensor location and spread of contaminants, using only the network topology. The vulnerability is a measure that indicates the most critical elements in the system, whose breakage imply structural disconnection and consequent malfunctions; the resilience is a global measure that indicates the robustness of the overall system considering its structural connectivity (Soldi et al., 2015). Furthermore, resilience and vulnerability of UDNs are also critical for the possibility of propagating cascade failures on other connected urban infrastructures (e.g., roads, gas network, telecommunications network, etc.), even with greater effects. The identification of the optimal monitoring nodes refers to the control of the system for various issues; the identification of the diffusion capacity of the various nodes supports control and identification of potential sources of target contaminants and pathogens. In the following analysis the tailored metrics are applied to the Extran network, in particular the in-Degree centrality (Equation 6a) for investigating vulnerability/resilience, the out-Harmonic (Equation 6b) for analyzing the spread of contaminants and the Betweenness centrality (Equations 6c and 6d) for studying optimal sensor location.

4.1.1. Vulnerability

The UDN vulnerability analysis can be carried out by removing nodes (or pipes) from the system and gradually evaluate its response. Obviously, the destruction of the system when subject to breakage also depends on its characteristics, both topological and operational. The objective of the CNT analysis with the use of the in-Degree centrality is to individuate the nodes that can generate the largest damage.

Referring to the Extran network, Figure 5a reports the in-Degree centrality embedding both relevance and direction for pipes. It shows that the in-Degree centrality values indicate the outfall (n10) with nodes n9 and n8, which share its same relevance, as the more important. This result suggests that the in-Degree centrality is good to analyze vulnerability of the node of the network.

4.1.2. Spread of Contaminant

Identifying the capacity of each node in spreading contaminant is crucial to control illicit intrusion and pathogenic diffusion. The CNT metric that better describes the ability of a node to diffuse contaminant into the network is the out-Harmonic centrality, representing the minimum distances between a target (contaminated) node and all the others. If an element can easily reach other elements, it means that it can easily spread the information, which can be more or less positive depending on what the information is. When the information is a contaminant, or even a virus (e.g., COVID 19), the metric could be useful in easily identifying the ways of the spreading. In conclusion,

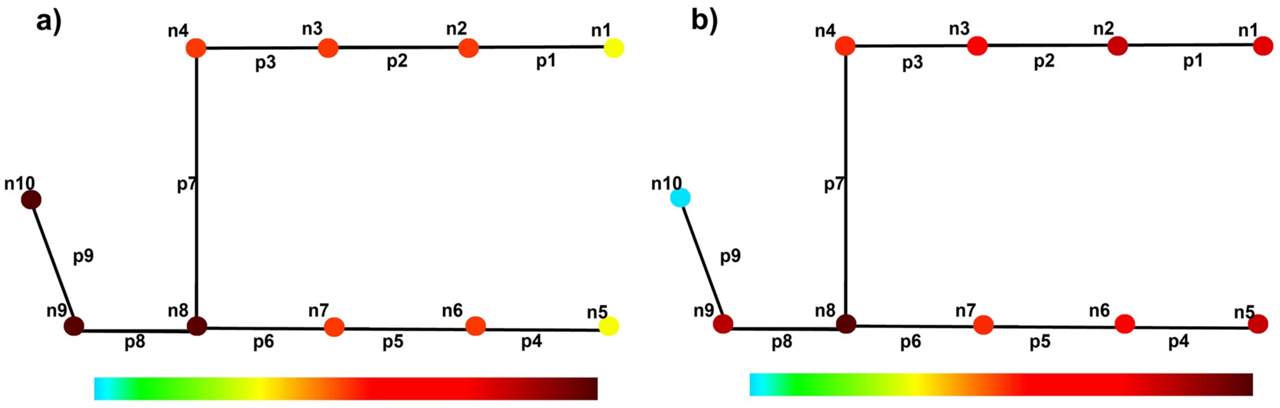

Figure 5. (a) In-Degree and (b) out-Harmonic centrality embedding both relevance and directions for pipes for Extran network.

the contaminant spread is well identified by this metric, which precisely figures out the process of information diffusion. Hence, the greater is the Harmonic of a node, the greater its contamination spread potential.

Embedding information about both relevance and flow direction, Figure 5b reports the out-Harmonic values, which identify the nodes n1, n5, and n8 as the more important in spreading contaminant. This result is indicative of the diffusive capacity of the nodes. A substance spilled in these nodes will surely be identified, while contaminant introduced in nodes with low metric values will have little chance of being disseminated and identified in the system. Furthermore, the results show that the outfall has null diffusive capacity, which is consistent with the operation of the system.

4.1.3. Optimal Sampling Design

The evaluation of the operation and performance of UDNs is usually based on measurements of flow rates and concentration of contaminants. Betweenness centrality and Edge betweenness centrality are potentially good metrics to individuate locations for sensors/sampling points, since it is higher as more the element is crossed.

Figure 6a reports the Betweenness centrality embedding both relevance and direction for pipes. It correctly identifies node n8 as the most central one, because it is the sole connection between three portions of the network, and it represents a sort of pivotal point, being the most traversed by the internal paths among those with the greatest relevance. Moreover, the second most important node is n9, the one close to the outfall. Then, the analysis indicates nodes n8, n9, and n4 as the most suitable for either hosting measuring instruments or locating sampling points. Figure 6b shows the Edge Betweenness values obtained considering both relevance and direction. It identifies the pipe p8 as the most important and suggests that the more critical sections to be monitored are p8, p9, p7, and p3. This outcome suggests that the metric defines a sort of path of importance in the network and shows

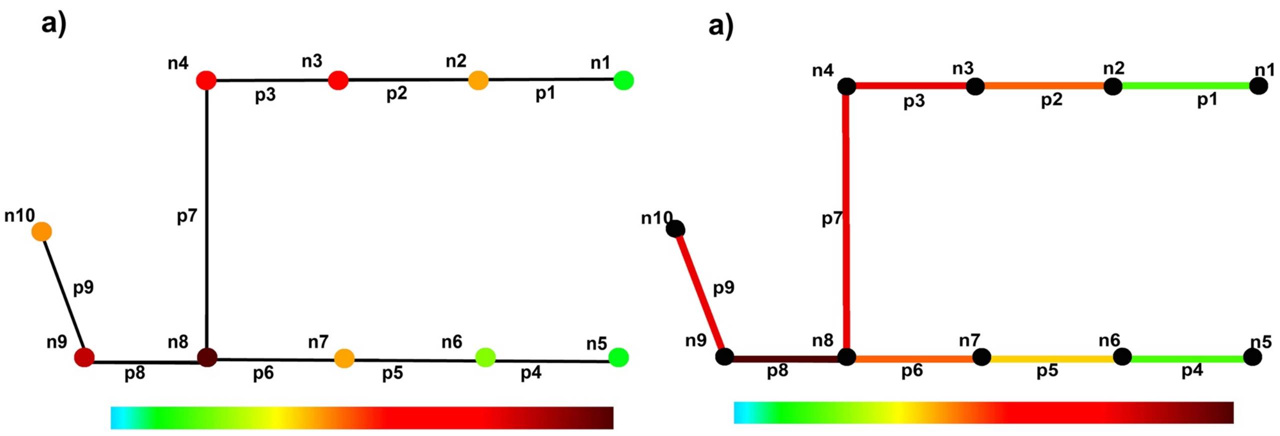

Figure 6. (a) Betweenness centrality and (b) Edge betweenness centrality embedding both relevance and directions for pipes for Extran network.

that the coupling and the interaction between topology and intrinsic relevance, together with the prior information about the flow direction, increase its performance.

5. Case Studies

The previous analysis has shown potentialities and applicability of CNT metrics to UDNs. While their use on simple schemes is trivial, when used on complex networks they provide useful information not clearly identifiable with the only knowledge of the topology. Their application on more complex networks is presented in the following paragraphs.

5.1. SWMM Example 3 Network

SWMM example 3 is a simple urban drainage network composed of 31 nodes, 32 pipes, 2 outfalls (node 32 and 33), 1 storage (node 34) and 1 pump. Its layout is reported in Figure 7a and the network data can be downloaded from the EPA website (https://www.epa.gov/water-research/strorm-water-management-model-swmm). Figure 7b shows the Horton's hierarchy of the network, characterized by three orders. The intrinsic relevance of each node is obtained, as for Extran network, reporting the hierarchy order to the nodes.

Figure 8 shows the standard metrics, while Figures 9 and 10 the tailored ones. Classic analysis assigns high metric values to many nodes, making difficult to assess their vulnerability and diffusion capacity, as well to obtain information on the optimal position for sensors.

Looking at the Tailored metrics in Figure 9, it is instead possible to glimpse how they better identify the behavior of the system. In terms of vulnerability analysis, the in-Degree (Figure 9a) immediately identifies the most important node with n18, which is the most relevant element because close to the main outfall and with higher degree of connection. The second most important element is node 34, which represents the most

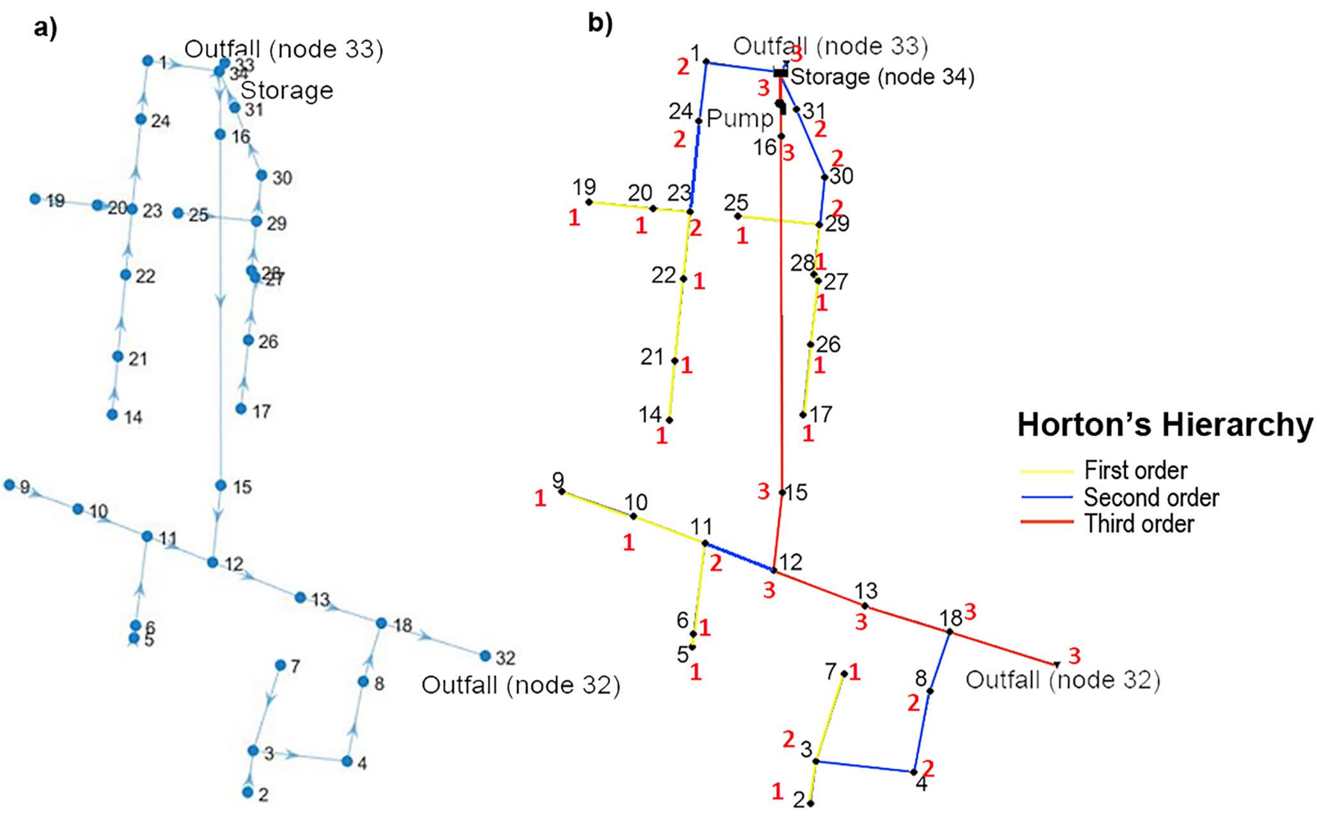

Figure 7. (a) Network layout with flow direction and (b) Horton's hierarchy for SWMM example 3 Network.

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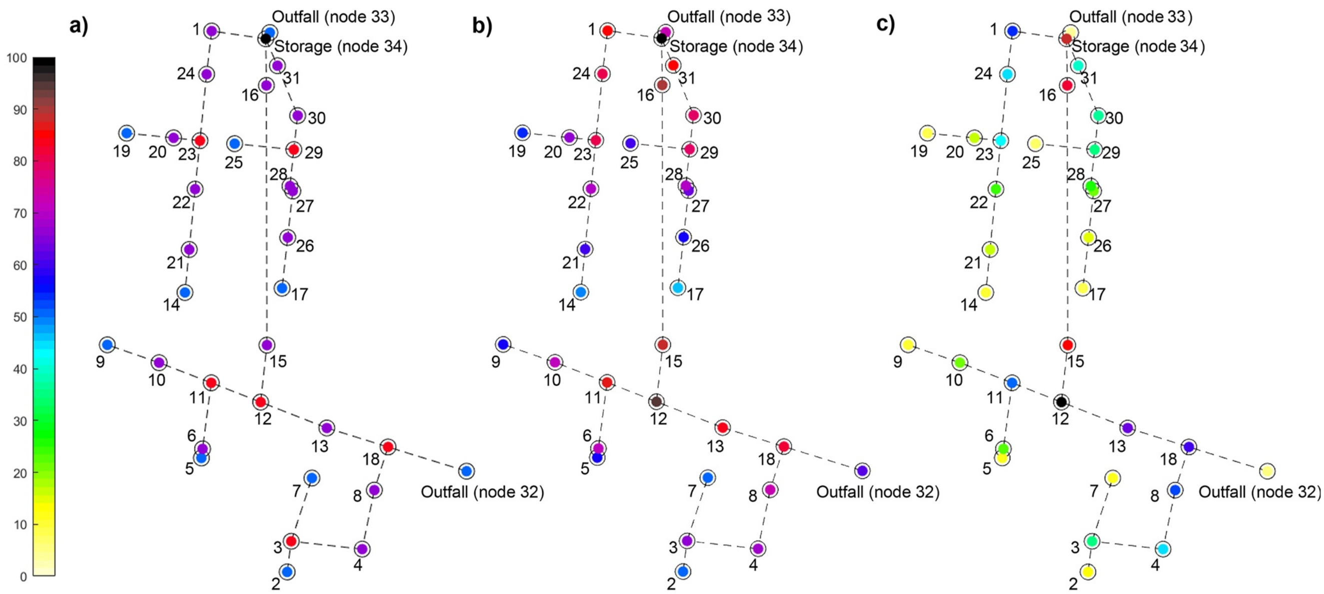

Figure 8. (a) Degree, (b) Harmonic and (c) Betweenness for SWMM example 3 Network.

connected node with high relevance. The presence of two outfalls in the network immediately indicates a lower vulnerability.

About the contaminant spreading, the out-Harmonic (Figure 9b) identifies the most important node with node 34, which has a high intrinsic relevance (equal to 3) and, more significantly, is directly connected to highly rele-

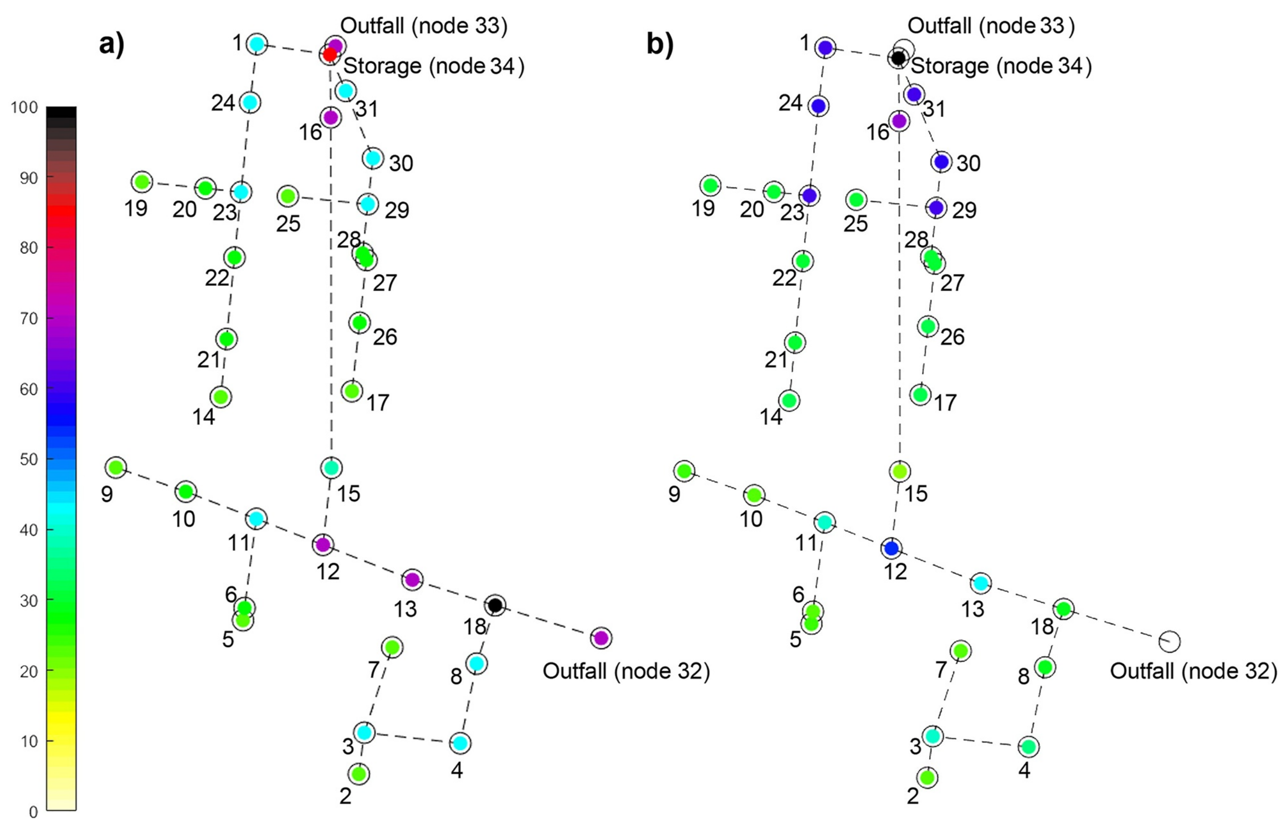

Figure 9. Tailored (a) in-Degree and (b) out-Harmonic centrality embedding the intrinsic relevance of nodes and directions for pipes for SWMM example 3 Network.

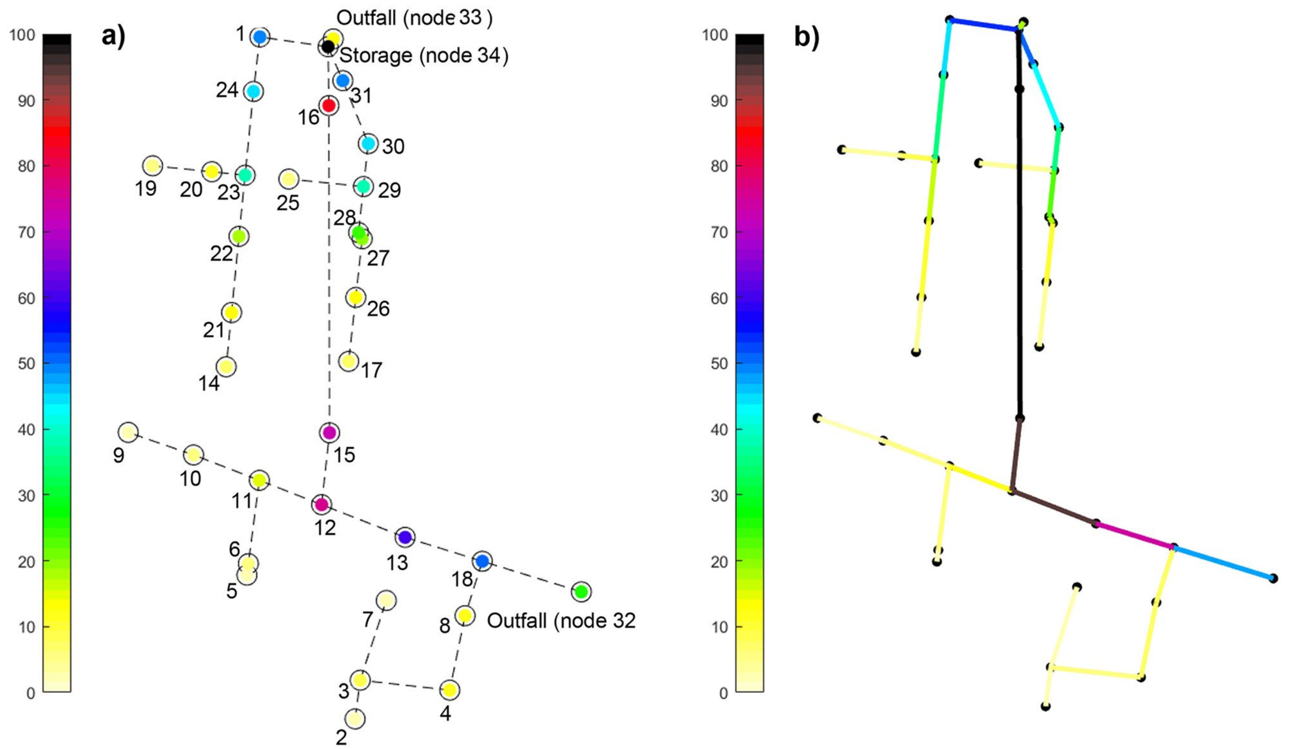

Figure 10. Tailored (a) Betweenness and (b) Edge betweenness embedding the intrinsic relevance of nodes and directions for pipes for SWMM example 3 Network.

vant nodes (nodes 1 and 31 with relevance equal to 2) from which obtains data to disseminate in the network (toward node 16). The diffusive capacity of some nodes is greater than that of other ones. Also in this case, the two outfalls have null diffusive capacity, because they receive the contaminant but cannot themselves spread it on the network.

In terms of monitoring design, the Betweenness (Figure 10a) identifies the most important node with node 34, that is, the most crossed element in the paths between nodes in the network. Its high connectivity (degree = 4) supports this result. The second most important element is node 16, followed by all the nodes directed to the main network outfall (node 32), indicating that this path is the most critical to monitor in the system. Coherently, focusing on pipes, the Edge Betweenness, reported in Figure 10b identifies the pipes linking nodes 33-16 and 16-15 as the most important. It also suggests that the more critical pipes to be monitored are located between nodes 33 and 32.

5.2. Massa Lubrense Network

Centrality metrics embedding the intrinsic relevance of nodes and directions for pipes are here applied to the Massa Lubrense network, a medium size real drainage network (Sambito et al., 2020) whose layout is reported in Figure 11.

The UDN has a length of 49 km, and it is composed of 1.723 pipes, 1.736 nodes, 13 pumps, 13 storages and 2 outfalls. The presence of all these devices and the presence of areas with different destinations (residential, commercial, and industrial) makes this system very complex. In this network, the Horton hierarchy is characterized by seven orders.

Figure 12 reports the tailored in-Degree centrality applied to the direct graph of the network. The ranking of nodes is obtained according to both their relevance and topological position. From a global point of view, the results of the analysis show that by increasing the importance of hydraulically relevant nodes (e.g., outfalls), hydraulic hubs are generated within the system, leading the networks toward an increasingly scale-free model (Barabási & Albert, 1999). This means that the network is characterized by few nodes with

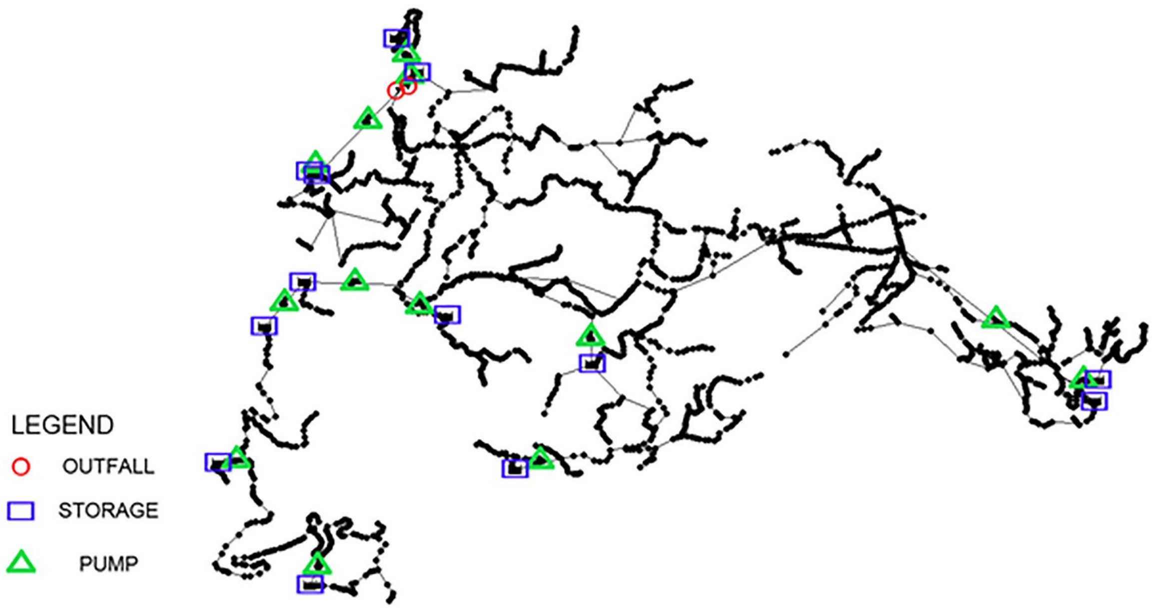

Figure 11. Layout of Massa Lubrense network.

high metric values (nodes from black to blue) and many nodes with low metric values (nodes from cian to light yellow). In terms of system vulnerability, removing a hub, that is a node with high metric value, leads to an immediate decrease in the system's operation, while, removing a less important node its capacity is almost unchanged.

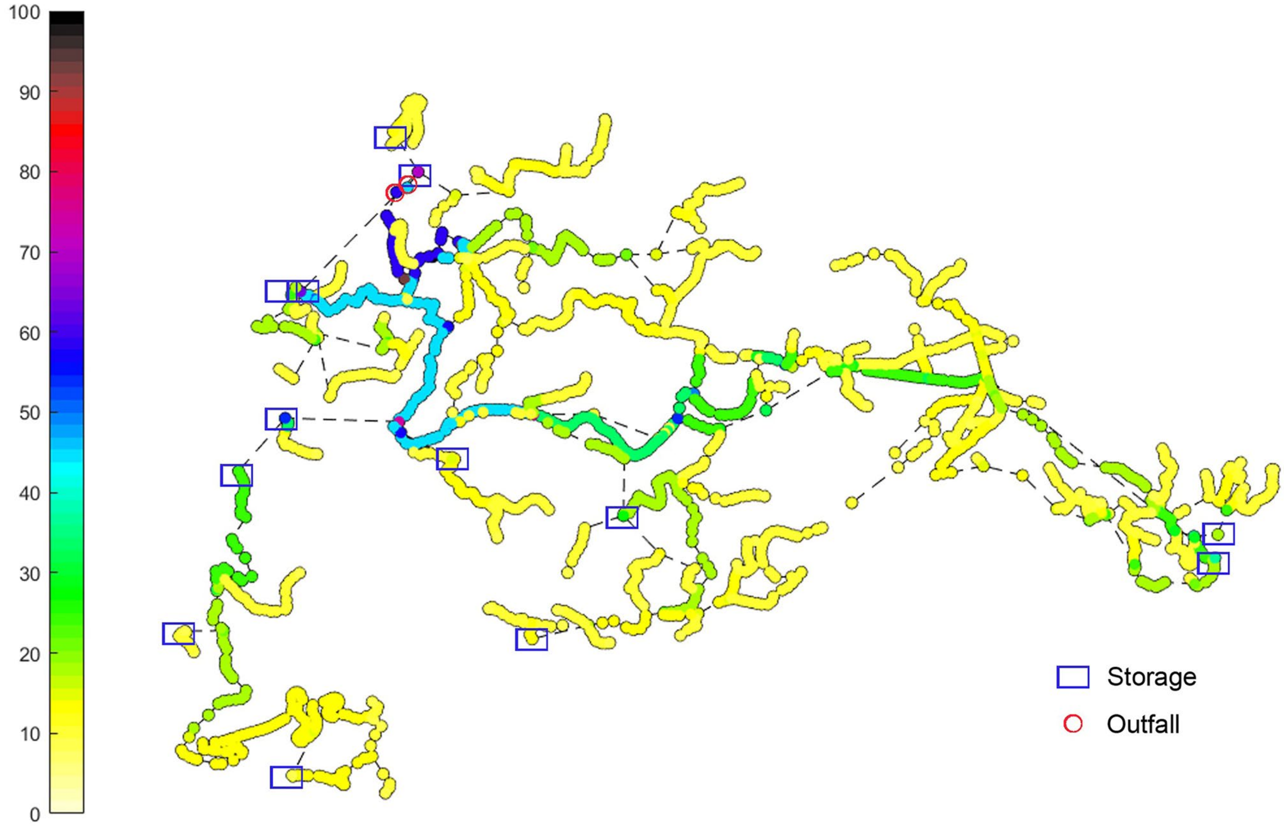

Figure 12. Tailored in-Degree centrality for Massa Lubrense network.

In particular, the results identify the most important nodes located in the upper left area of the system, close to the two outfalls (black nodes). They have the higher value of the metric because they are very connected in addition to the maximum intrinsic relevance (derived from the Horton hierarchy). It is possible to notice the presence of relatively important nodes also within the system (blue nodes), whose relevance is always a combination of topology and intrinsic relevance. Technically speaking, the system is very vulnerable with respect to attack on the important nodes, for example, outfall and nodes close to it, whose damage could significantly compromise its functioning.

Figure 13 reports the tailored out-Harmonic centrality. As said, the tailored out-Harmonic considers the information that comes out from a node, and therefore identifies the nodes that disseminate large amounts of information in the network. The ranking of nodes is indicative of its ability to diffuse information to other nodes. Therefore, the metric is able to assess the capacity of the various areas of the network with respect to the diffusion of contaminants, which is important to study the spreading of target substances and pathogens (e.g., drugs, SARS COV 2) and to contrast illicit intrusions.

Figure 13 shows that the out-Harmonic identifies the nodes with the highest diffusive capacity in the upper left, central and lower right areas, along the main backbone of the system. Many of them have medium-high intrinsic relevance values and are, in turn, connected to very relevant nodes, from which they acquire data to disseminate in the network. Each node can disseminate information only to adjacent nodes and the diffusive capacity of some nodes is greater due to their topological relevance. Obviously, once the nodes with the highest value of the metric in the various areas of the system have been established, their adjacent nodes gradually assume lower values unless they connect with other nodes with high out-Harmonic centrality values. This behavior permits to outline the diffusion paths in the system and highlights the fact that the main transfer component takes place on them. The two outfalls have null metric value, not being able to spread anything downstream. From a technical point of view, the metric identifies the nodes with the highest diffusion capacity.

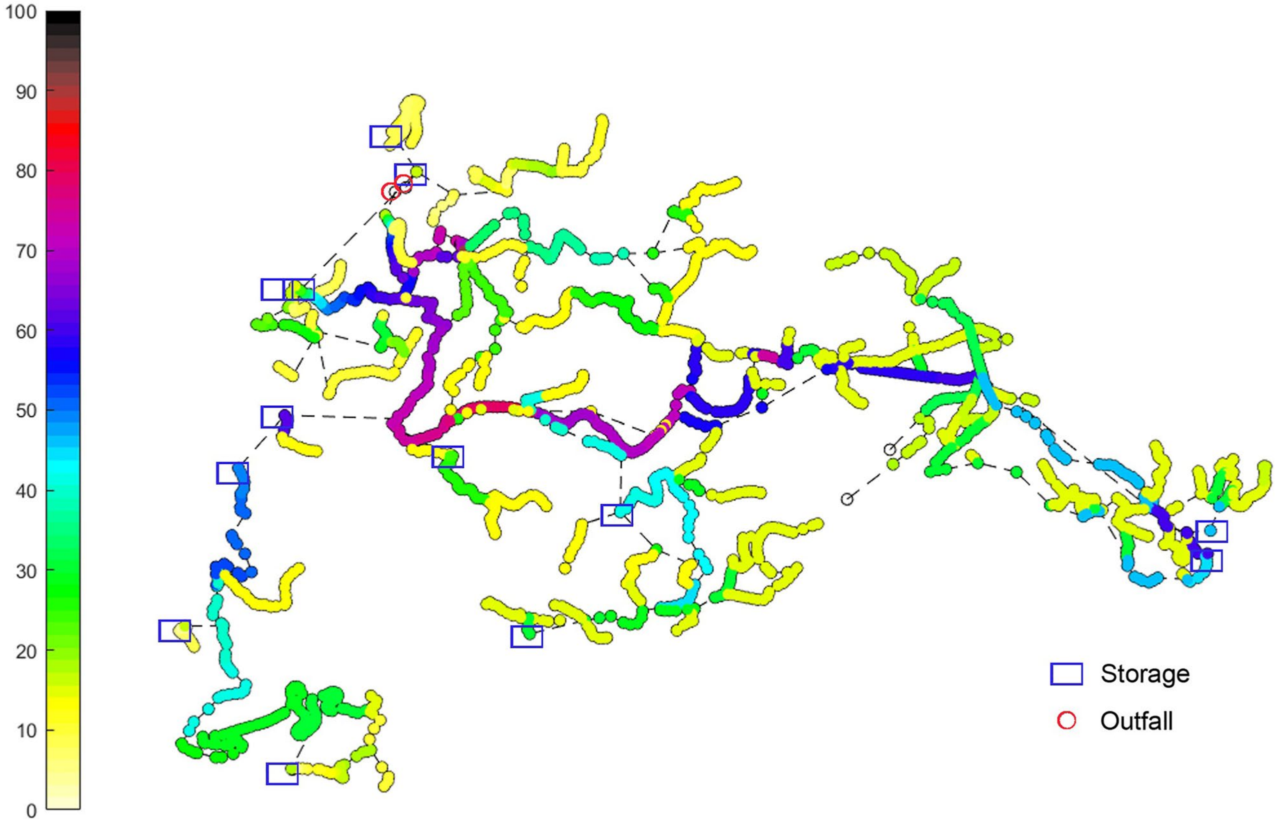

Figure 13. Tailored Out-Harmonic centrality for Massa Lubrense network.

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Figures 14 and 15 report the tailored Betweenness and the tailored Edge Betweenness centrality applied to the direct graph of the network respectively. These metrics identify the most traversed elements in the direct paths between couples of nodes.

Results highlight the presence of an important path from the right side of the network to the left side, toward the outfalls. The highest values of the metric are in the main confluences of the system and in the elements located downstream them. In these nodes, their intrinsic relevance increases (increasing the order of the Horton hierarchy) and the majority of the shortest paths pass from them to reach the outfalls. In this sense, the metrics identify the bridges of the system, that represent the main connections between the various portions of the network or the connections between the different areas and the primary sewage system, where large amounts of information pass before reaching the outfall.

Both figures suggest that the most critical elements useful to monitor the network functioning are located mainly on the backbone of the network, even if it is possible to identify other strategic elements scattered throughout the system. For example, the magenta circle in Figure 14 indicates a node whose metric value is very high. Its importance is attributable to both the topological component, having a degree of connection equal to 4, and to its high intrinsic relevance, collecting the information coming from three different paths, one of which particularly influential. The results are similar for the tailored Edge betweenness in Figure 15. The orange circle indicates a pipe with a very high metric value, located downstream of a relevant confluence, where three portions of the network, two with medium-high importance, enter.

From a technical point of view this analysis suggests which elements represent good candidates for hosting measuring devices for the realization of measuring districts, useful for monitoring hydraulic quantities.

The performed analysis with CNT tailored metrics has the advantage of using exclusively topological information, without the necessity of hydraulic simulation and then it is applicable from the initial phases of the study of the system (i.e., after the topological survey).

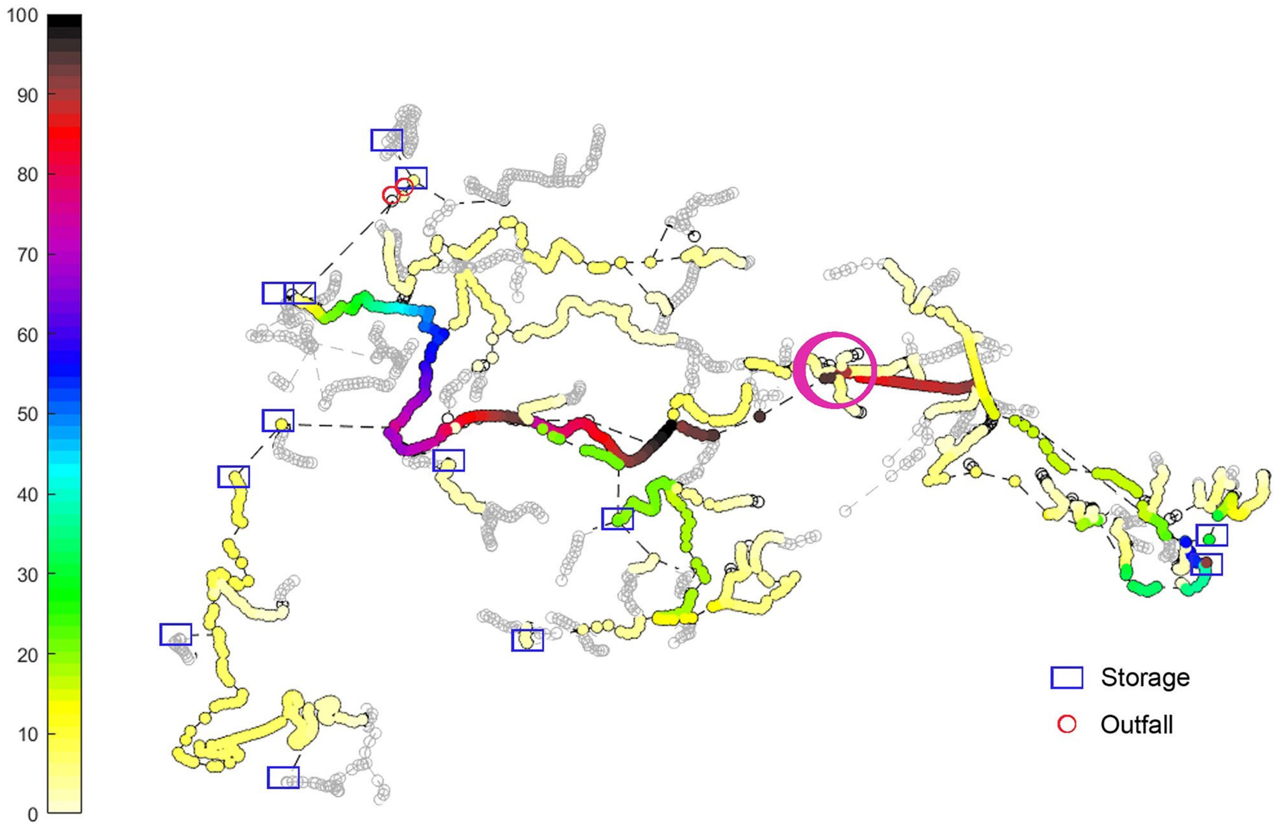

Figure 14. Tailored Betweenness centrality for Massa Lubrense.

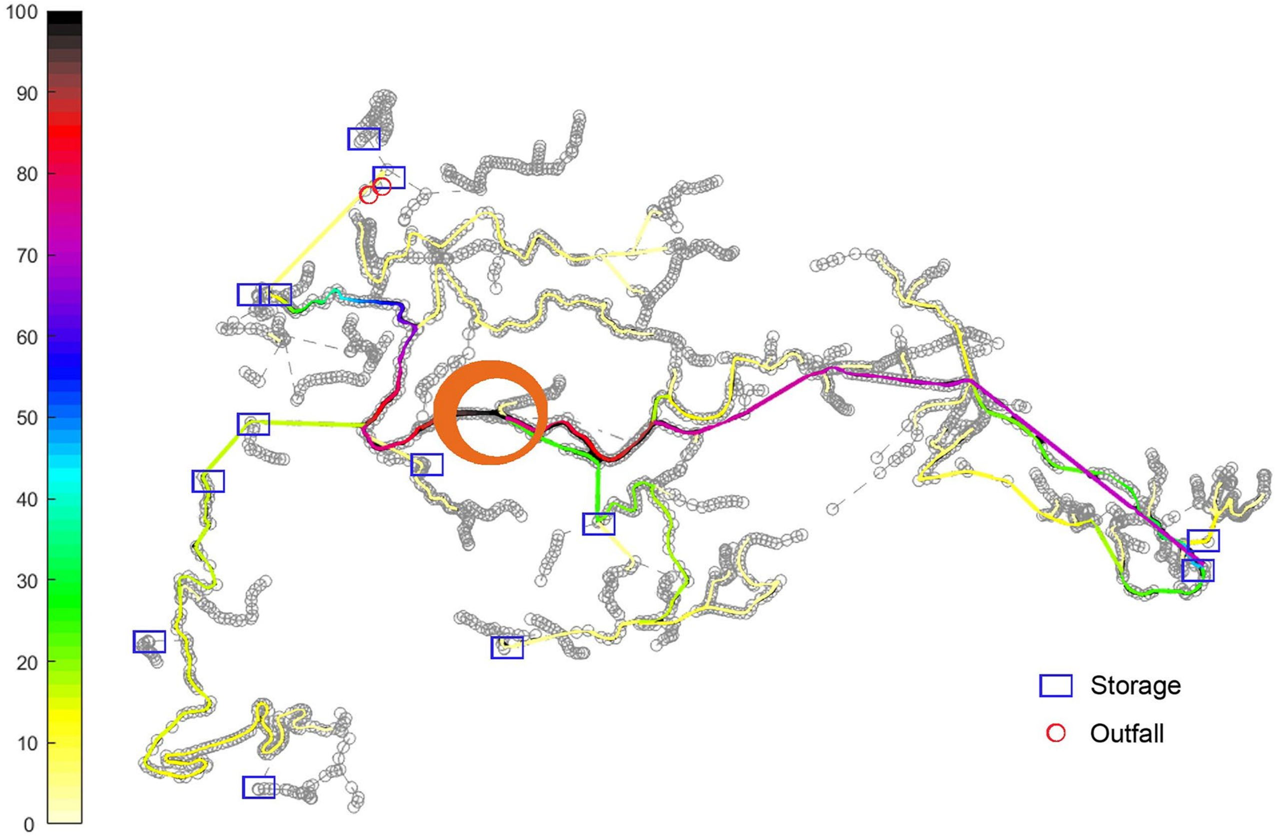

Figure 15. Tailored Edge Betweenness centrality for Massa Lubrense network.

This approach does not embed the hydraulic behavior, so that the analysis doesn't provide a detailed description of dilution and decay processes. The use of Horton's hierarchy as relevance allows only a preliminary analysis, because the gap in terms of relevance between outfall (hydraulic hub) and nodes in the network is not correctly underlined, presenting all nodes the same order of magnitude. Obviously, embedding hydraulic characteristics as intrinsic relevance could enhances the analysis.

In conclusion, the presented study proposes a preliminary and complementary tool to study UDNs. So, in the line to follow for realizing interventions, which goes from their planning to their execution, the proposed strategy already in the preliminary phase provides valuable information on where to intervene depending on the problem to be faced.

6. Conclusions

UDNs represent critical infrastructural systems conditioned by spatial factors, tree-like connective structure and flow direction imposed by the slope. The choice of resorting to the CNT tools for the UDN analysis is related to the need of solving different critical tasks, such the evaluation of network vulnerability and resilience, the individuation of illicit intrusion and the control of the presence of target substances for either environmental or epidemiological purposes. The idea is to use CNT metrics to provide a realistic preliminary analysis regardless of the system operation. This can be very useful to analyze complex networks, often not well known or entailing high data uncertainty and modeling problems. The potentialities of CNT tools for UDN analysis are tested using both classical centrality metrics (in-Degree, Betweenness and out-Harmonic), and tailored centrality metrics, embedding prior information as intrinsic relevance of each node and flow direction, which derive from the Horton's hierarchy and geometric data (pipe slope), respectively.

Results shown that standard Degree, Betweenness and Harmonic are not able to represent the network behavior, while the tailored metrics provide useful information in determining vulnerability/resilience and for planning monitoring strategies.

Overall, the work highlighted the importance of topology in the study of UDNs and how the actual behavior of such systems is the result of the interaction between intrinsic relevance of nodes and network topology. This application represents a step toward future application for a better management of UDNs using CNT tools, instead of more complex and computationally expensive methodologies, requiring hydraulic simulation.

Data Availability Statement

The present work describe a new proposed approach and the analyses of two drainage systems. The data of the SWMM Example3 Network can be downloaded freeware from the site https://www.epa.gov/water-research/storm-water-management-model-swmm. A description of the Massa Lubrense network topology can be found in the work of Sambito et al. (2020), while the detailed geometric data furnished by the GORI S. p.a. Water Company cannot be disclosed as they are sensitive. The implementation of the used metrics and the analysis of the data were carried out with MATLAB R2021b, available under license on https://it.mathworks.com/products/matlab.html. In this specific case, the software is licensed by the University of Naples, Federico II.

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