

# Exploring the Interdependencies Between Transportation and Stormwater Networks: The Case of Norman, Oklahoma

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H. M. Imran Kays<sup>1</sup> , Arif Mohaimin Sadri<sup>1</sup> , K. K. “Muralee” Muraleetharan<sup>1</sup> , P. Scott Harvey<sup>1</sup> , and Gerald

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## Research Article

The significance of critical infrastructure systems in maintaining productivity is undeniable. However, such systems remain susceptible to external disturbances and cascading failures. Instead of operating independently, these physical systems, such as transportation and stormwater systems, form an interdependent system. This interdependence, particularly important during flooding, illustrates that the failure of a stormwater system can disrupt traffic networks. To explore the extent of such interdependency, this study investigates the transportation and stormwater networks in Norman, Oklahoma. Using network science theories and concepts of multilayered networks, this paper analyzes these systems, both individually and in combination. The study identifies closely located components in the road and stormwater networks using Moran's I spatial autocorrelation metric. Next, the connectivity of these networks is represented in a graph format to investigate the topological credentials (i.e., rank of relative importance) of the network components (i.e., water inlets, road intersections as nodes, and stormwater conduits, road segments as links). Moreover, such credentials further change by considering the weights of the network components (i.e., average daily traffic, water flow). The proximity-based connectivity considerations between these networks utilizing Moran's I significance score revealed a good indicator of spatial interdependency. When incorporating directionality, the multilayer network analysis highlights that highly central components tend to cluster spatially, unlike the undirected counterpart. The study also identifies vulnerable locations and network components in a combined network setting that differ from the networks in isolation. In doing so, the research reveals new insights governing the complex reliance of transportation systems on neighboring stormwater systems.

## Keywords

interdependent systems, spatial interdependency, topological credentials, multilayer network, network resilience, transportation, stormwater networks

A. Miller<sup>1</sup>

## Abstract

Transportation Research Record  
tion, stormwater networks

Infrastructure functionality, both physical and virtual, is crucial to the smooth operation of urban life.

Specifically, 16 critical infrastructures are defined by the U.S. Department of Homeland Security (DHS) to have an important role in national safety, economy, and public health (1). These infrastructures behave like connected and

interdependent systems that affect each other's performance (2). This idea changes the traditional way of exploring individual system problems into a multistage problem. The connections between linked infrastructures can be seen as operational, functional, geographic, or logical relationships. For example, some systems interact directly (e.g., power and communication), some show cyber or informational interdependency where the rule of connection is information sharing (e.g., transportation and power), and some infrastructures have geographic

<sup>1</sup>School of Civil Engineering & Environmental Science, University of Oklahoma, Norman, OK

Corresponding Author:

Arif Mohaimin Sadri, sadri@ou.edu

interdependency where the systems are connected through spatial colocation (e.g., transportation and water networks). Infrastructures have logical or policy related interdependency where similar components affect the connected systems (e.g., transportation and financial services sector) (3–6). In addition, the intra- and intersystem relationships are highly dynamic and localized in nature which creates cascading or compounding failures of systems when exposed to natural hazards (7). One of the challenges for research is to define and quantify the systems' integrated behavior that translates complete dependency as well as vulnerability information into a logical framework.

Transportation infrastructure is a critical lifeline service that contributes to the sustainability and resilience aspects of society (8, 9). The nature of transportation infrastructure is to provide connectivity that physically helps other systems to maintain normal operation. For example, power distribution lines, underground water distribution, wastewater, and stormwater lines follow the road network, which represents the physical dependency and spatial colocation aspects of connectivity. The financial, economic, chemical, and agricultural sectors also require connectivity using the transportation network (logical and indirect dependency characteristics of connectivity) (2, 10). On the other hand, the urban water system, particularly the stormwater network, has great importance in the built environment against pluvial surface flooding (defined as flooding induced by excessive precipitation beyond the capacity of the stormwater drainage system) (11). Having spatial colocation with the transportation network, failure in the stormwater network may lead to flooding in the road network (3, 12). On the other hand, the transportation network can be used to carry emergency management personnel, raw materials, and goods to manage and repair the stormwater network (13). In addition, sometimes parking lots are used as water retention areas during flash flooding in some cities (14). These examples provide enough evidence to confirm the functional and geospatial interdependency of transportation and stormwater systems in the urban environment. Moreover, these infrastructures are identified as critical infrastructure by DHS (1). Given that they are an important part of lifeline services, this paper aims at exploring aspects of the interdependency of transportation and stormwater networks.

Since the concept of infrastructure connectedness took shape in scientific research, numerous approaches and frameworks have been developed to model the aspects of

interdependency. Consequently, Sun et al. categorized these methods based on dependency characteristics, interaction rules, and data driven approaches, also described their scale and complexity of application

(4). Several quantitative approaches (i.e., graph-based, input–output-based, agent-based, system dynamics-based, Bayesian network-based, optimization-based, and econometric-based models), were adopted in previous studies where, however, the accuracy and outcomes were compromised by incomplete information about the interdependency (15). Real-world systems have numerous drivers and even more tensions between them, so solutions for one set of drivers may not be good enough for others. Therefore, it is difficult to establish a deterministic solution (perfect solution) to this problem (16). Likewise, modeling of transportation and stormwater system interdependency is compromised by (a) unavailability of high resolution topological and operational data which is not publicly accessible and (b) incomplete understanding of instabilities and vulnerabilities in both spatial and functional settings. Research challenges also exist as a result of the lack of a comprehensive, calibrated, and validated decision support framework for practitioners. These research gaps motivated the authors to investigate the interdependency behavior of transportation and stormwater networks with an in-depth network-based analysis. Therefore, the research goal of this paper is to investigate the functional and spatial interdependency of transportation and stormwater systems. The objectives to satisfy the goal are threefold: (i) to explore the spatial interdependency of transportation and stormwater networks, (ii) to investigate the aggregate behavior of these systems when spatial, functional, and connectivity metrics are combined, and (iii) to compare the individual and multilayer networks' topological credentials to observe the change in properties resulting from interdependency. The topological credential of a network is defined as the quantification of criticality and vulnerability of its components (e.g., nodes and edges) based on their topology in the network by applying network metrics (e.g., degree, centrality) (17). This paper will answer the following research questions:

To what spatial level are the transportation and stormwater systems interdependent?

What is the best indicator of spatial interdependency?

What is the best way to incorporate functional and spatial interdependencies?

What is the best analysis framework to capture interdependency?

How do the topological credentials change from individual level to multilayer network?

Figure 1 shows the hypothetical graph presentation of the transportation ( $G_1$ ) and stormwater ( $G_2$ ) networks. A graph or network is a mathematical form of representing the structure of a complex system, where the nodes mean individual entities and the links or edges represent the relationships between them (18). In Figure 1 the nodes T and W show the entities in  $G_1$  and  $G_2$ . Additionally, multilayer network ( $G_m$ ) is represented by connecting these two networks with red edges (W3–T3, and W4–T4) which represent distinct types of relationship within transportation and stormwater networks. For example,

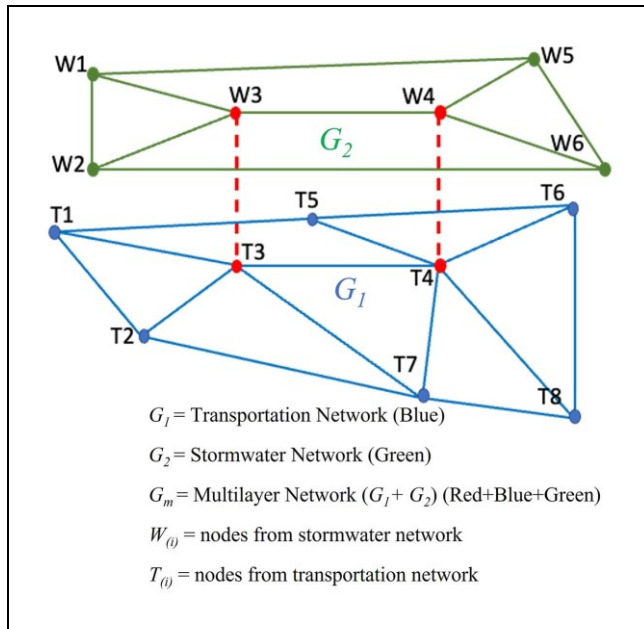


Figure 1. Conceptual figure representing transportation, and stormwater systems, and their multilayer network.

stormwater is routed from the road to the stormwater network using inlets, manholes, junctions, and side drains (T3!W3). On the other hand, emergency crews need to use the road network to access junctions via manholes (W3!T3) for maintenance. Therefore, the edge between T and W can be used to explain this functional interdependency. The main difference between the individual and multilayer network is the connectivity (link or edge); while all nodes and edges in a single layer network represent the same relationships, different nodes and edges have different properties in a multilayer network. Moreover, a multilayer network is different from the aggregated network (Figure 2). For this study, multilayer network metrics will be used instead of aggregated network, which has some limitations (explained in a later section) in representing realworld networks (19).

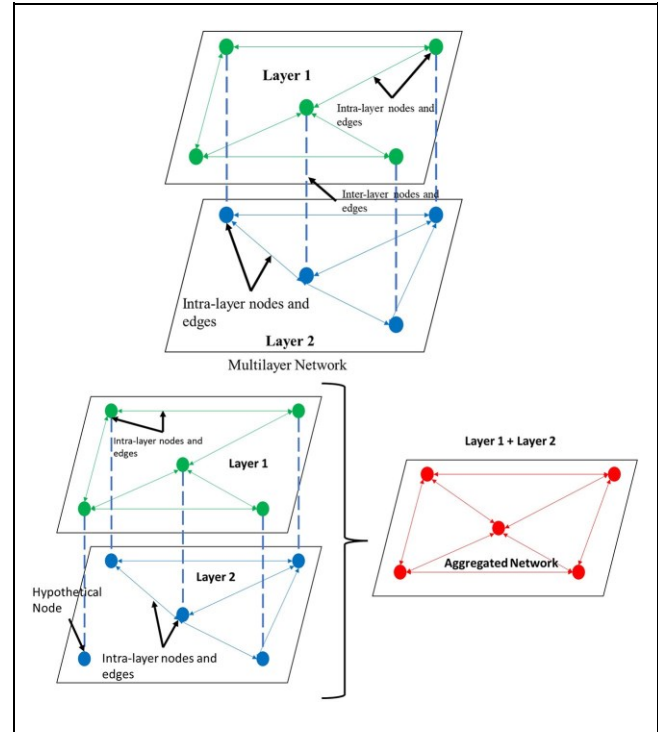
The paper is organized as follows: the second section offers a brief but critical literature review of existing

research and modeling approaches. The third section discusses the data source, structuring, and manipulation. The fourth section discusses the methodology and results. The final section concluded the paper by discussing the key findings and future research scope.

Figure 2. Multilayer network and aggregated network.

## Literature Review Interdependency of Infrastructures

Researchers have been actively investigating the complexities



of systems' interdependencies for over 20 years. Physical systems have numerous drivers, and it is difficult to find the perfect solution for all. The localized and dynamic behavior of systems, and their probabilistic likelihood of failure, makes it challenging to combine the story in a single framework. As such, recent studies emphasize the research need for modeling the systems' interdependency, particularly focusing on capturing cascading, escalating, or compounding failures. Rinaldi et al. in 2001 proposed an outline where they categorize interdependency, failure mode, logical interfaces, and other aspects in a comprehensive framework (3). Likewise, Zimmerman (5), Dudenhoefter et al. (20), Zhang and Peeta (6), and Sharkey et al. (21) classify interdependency from different perspectives; some classifications are based on systems' functionalities, reaction to natural hazards, restoration, or economic impacts. Some other studies (22–25) focus on the resilience of infrastructures against natural disasters and human threats and propose frameworks to show the response of

connected systems to these situations when human, environmental, and system performance and adaptivity are combined. State-of-the-art literature suggests the significant importance of analyzing infrastructures as connected systems rather than an individual entity.

Many modeling approaches have been proposed for studying interdependency in the literature. These approaches vary based on the type of system, availability of data, and quantifying metrics. Ouyang classified these modeling techniques into six categories: empirical approaches, agent-based modeling, system dynamics, economic theory-based modeling, network-based, and other modeling approaches (15). That study also summarized the data needs, fundamental considerations, and computational efficiencies of different modeling approaches. Similarly, Sun et al. classified the modeling approaches into three categories: the dependency table (i.e., includes qualitative and quantitative surveys), interaction rules (i.e., includes discrete event simulation, agent-based model, system dynamics, Bayesian-networkbased models, optimization, mobility model, aggregate supply-demand model), and data driven approaches (i.e., supervised and deep learning, text mining, etc.) (4). Some of the applications of these interdependency modeling approaches are discussed in the following sections.

McDaniels et al. developed an empirical framework to capture interdependencies of power, buildings, water, health, and road transportation systems for the 2003 North American blackout, 1998 ice storm, and 2004 Hurricane Charley events by using big data and hierarchical representation of systems (26). The concept of hierarchy resembles the process of cascading and escalating failure between systems; however, failure in real systems does not always maintain hierarchy, which limits the application of this method for the study of interdependency. Aghababari and Koliou developed an agent-based model (ABM) to simulate the subsystems of an education infrastructure on the occasion of a tornado event and predicted the response of agents in schools, households, construction companies, and power and water supply systems (27). Oliva et al. also proposed an agent-based input–output model that provides a detailed framework considering the exchange of resources between infrastructures as an explicit parameter where the functionality loss is used as an internal parameter (28). These studies show that ABM generates reliable results in interdependency modeling yet the requirement of big data to calibrate and validate the model limits its application. Additionally, ABM performs microscopic analysis which represents a big computational challenge.

One of the most popular interdependency modeling frameworks is graph-based network modeling. Johansson and Hassel modeled the propagation of disturbance in a railway system using a network-based approach and identified the vulnerabilities and performances of all the subsystems (29).

Wang et al. proposed a network modeling framework to analyze the vulnerability of interdependent infrastructure systems for the major cities in China and performed case studies for power and water systems. Critical and vulnerable components of the connected infrastructures are identified and ranked by this framework (30). Similarly, Chai et al. analyzed the characteristics of the critical infrastructure networks and identified “Oil & Gas,” “Information & Communication Technologies (ICT),” and “Electricity” infrastructures as the most important infrastructures on which the performance of other infrastructures depends. By using network modeling, the study found that these infrastructures have the potential to cause the greatest cascading failure (31). Zhang and Peeta developed the multilayer infrastructure network with spatial computable general equilibrium (MIN(S)CGE) modeling framework to capture the interdependencies in the transportation sector, where they mainly focused on policy implementation scenarios and their effect on the system (6). That study did not include comprehensive information about the propagation of natural disasters or human-caused disturbances in the framework; however, the model demonstrated how to include policy implementation within the interdependent system operation. Sharm and Gardoni developed a mathematical framework using interface function along with network modeling and tested the model on a regional scale for post-earthquake recovery of interdependent power and water infrastructures (32). In summary, these studies exhibit the potential of a network-based modeling framework to express the interdependency of connected and dependent infrastructures provided overall system information is available. Though a graph-based approach requires big data to model the system, this modeling technique has the potential to represent the system’s connectivity better than ABM. An integration of ABM with graph-based approach will make a better modeling framework to predict scenarios based on policy implications.

## Interdependency of Stormwater and Transportation Networks

Few studies are found in the literature that analyzed the interdependency of stormwater and road networks during adverse weather and natural disasters. AbdelMottaleb and Zhang combined the transportation and water distribution networks based on their spatial interdependency and developed a combined interface graph considering their connected and vulnerable locations (33). Using the random forest technique, that study predicted the connectivity clusters that explained the spatial interdependency; however, the developed giant component captured only 17% of the interface network connectivity which weakened the analysis. Also, other graph metrics were not explored in

the study which would have indicated the changed graph properties and interdependency during normal operation. Dong et al. investigated the failure propagation between road and sewer networks after an earthquake using graph percolation theory (34). This modeling approach can estimate connectivity failures with better accuracy but is computationally expensive and data intensive. Dong et al. used the Bayesian network modeling technique to quantify the failure of a road network from flooding from the neighboring channel but did not explain the critical locations and vulnerable components (35). In another study, Dong et al. developed a graph-based modeling framework considering the structural, functional, and topological vulnerabilities of road connectivity using network percolation theory in the context of a flooding situation (36). This framework captures the changing travel pattern during flooding, but macroscopic level giant component analysis was unable to pinpoint or set criteria to find locations of compounding failure. Atef et al. proposed a framework using neighborhood centrality and point variance to capture spatial and functional interdependence of water mains and transportation network (37). That study also lacked identification of the components' vulnerability and proper validation.

Some other studies have also explored the interdependence of road and water systems using different modeling approaches. Aslani and Mohebbi developed a resilience assessment framework using a geographically weighted regression (GWR) model to predict the combined resilience of interdependent water and transportation networks (38). Though the GWR integrates spatial attribute to regression and generates indicators, it is difficult to interpret the results for practical applications. On the other hand, fragility curves are also used for vulnerability analysis which expresses the probability of failure of the system's components for a specific disaster scenario. For transportation and stormwater networks, the fragility curve is not explicitly defined in the literature, yet some modeling approaches estimate the failure probability of infrastructure components based on the influencing factors. Mazumder et al. used 14 such factors to estimate the economic, operational, environmental, and social consequences of water and road segment failures. The study used fuzzy hierarchical interface which only utilized the joint probability of failure (39). For systemwide aggregate analysis, this type of econometric modeling is a good fit. However, unlike microscopic level analysis, aggregate modeling frameworks cannot identify the critical components which are vulnerable to disruption and might initiate cascading failure between systems. Graph-based network modeling is more appropriate for this kind of analysis.

Based on the review above, there is a literature gap in the area of an interdependency modeling framework for transportation and stormwater networks that supports the integration of spatial and functional indicators and application of network metrics to model the combined systems' performance. This paper presents an in-depth analysis to overcome these challenges.

## Review of Graph Metrics

The concept of graph (G) developed from the connectivity of components in different systems, which include physical, biological, virtual, and social systems. In graph, system components are expressed with two terms: nodes (n) and links or edges (e). For decades, many graph tools have been utilized to explain the connectivity between components. Most real-world networks do not exhibit either discrete or random patterns of connections, long tail in degree distribution, high clustering coefficient, assortativity, and so forth, which makes them complex networks (40). In general, a single layer of a network is represented by nodes and edges explaining the same type properties  $G[n,e]$ ; for example, in a transportation network, nodes and edges can be defined as intersections and road segments respectively (39, 56, 57). Also, graphs can be directed or undirected. When the edges of a graph have the property to express the direction of information flow, it is defined as directed graph (e.g., the direction of traffic flow in a road segment); on the contrary, if the edges represent both-way information flow, it is defined as undirected graph (e.g., both-way traffic in a road segment). But this representation sometimes misleads analysis when it presents more than one property of any connection; so the concept of multilayer representation of networks came to light that can represent different properties of the same entity in different layers. For example, between two intersections there can be transit and drive routes. Two separate networks are necessary to represent these two systems where the nodes (intersections) are same.

In a multiplex network, the nodes remain the same but the edges (representing connections based on a specific property) between them are different. There can be more than one different edges between nodes in a multiplex network; for example, in a social network, the connection between two persons can be friendship as well as business partnership. For a multilayer network, two or more networks are connected by interlayer edges (different than individual networks). For example, a road network and a stormwater network can be represented as a multilayer network where these networks can be connected by interlayer edges (which may represent interdependent network vulnerability or reliability) (41). Because of computational challenges, sometimes a multilayer network is aggregated for easier tensor representation. But this technique does not always represent the correct topology of the

networks. For example, an aggregated network sometimes creates hypothetical nodes and edges which makes all the networks' topology uniform (Figure 2). This approach may generate misleading insights. Although developing and analyzing a multilayer network is computationally expensive, it is a more realistic representation of real systems (19). Moreover, this approach is further enhanced by facilitating spatially embedded network analysis (42). Given such advantages, this study considers the multilayer network approach.

Significant research efforts have been made to explore the structures, topology, and nature of networks with innovative tools, theories, and metrics; yet this is still an open research area for real-world application (43). Some of the graph metrics used in this study that exhibit the properties of single and multilayer networks are discussed below.

### Degree

The degree of a node is the number of edges that are connected to it. For a directed graph, degree is expressed as the summation of in-degree (number of edges coming to the node) and out-degree (number of edges going out from the node). For adjacency matrix  $A_{ij}$  (the structure of the graph in the matrix), degree ( $D_i$ ) is:

$$D_i = \sum_{j=1}^{X_n} A_{ij}$$

For a multilayer scenario, the definition of degree is the same but represents with adjacency tensor  $M$  and decomposing multidimensional tensor as (44):

$$D_i = \sum_j B_{ij} U_j \quad (44)$$

where  $B$  is binary function and  $U$  is multidimensional rank-2 tensor.

### Degree Distribution

In real networks, degree distribution follows power law with long right skewed tail distribution. This represents the presence of higher degree nodes, but they are few in number; on the other hand, higher number and lower degree nodes are connected to the hubs and make the network dynamics. This attribute validates the scale free property of the network (45). The same behavior is observed for single- and multi-layer networks (46).

### Density

Network density is the ratio of actual connection to all potential connections. This metric gives an idea of having options for

potential connection between nodes. For a single layer network, density of graph  $G[n,e]$  is expressed as in Malek et al. (47):

$$\text{Density} = \frac{2e}{n(n-1)} \quad \text{for undirected network}$$

$$\text{Density} = \frac{e}{n(n-1)} \quad \text{for directed network}$$

$$\text{Density} = \frac{P_{\text{intra}} + P_{\text{inter}}}{n_i(n_i-1) + \sum_{j=1}^{l-1} n_j(n_j-1)} \quad \text{For multilayer network}$$

### Diameter

The diameter of a network is expressed as the size of longest shortest path between nodes. It represents the linear size of the network; a larger diameter represents longer connectivity to access nodes (48).

### Eigenvector Centrality

The eigenvector centrality (EC) of a node measures its relative influence in the network. This estimation is based on the importance of neighboring nodes and their influence (49). Calculation of EC is based on finding the leading eigenvector and expressed as:

$$EC = \frac{1}{k_1} \sum_j A_{ij} x_j \quad (49)$$

where  $k_1$  is the largest eigenvalue of adjacency matrix  $A$ .  $A_{ij}$  is the adjacency matrix and for multilayer network it is the higher rank adjacency tensor. The advantage of EC is that the value depends on the summation of neighboring values; large EC value indicates that the node is surrounded by many important neighbors.

### Betweenness Centrality

Betweenness centrality (BC) of nodes is defined as the number of shortest paths in the network that pass through that node. The node that more frequently sits on the shortest paths has a higher BC value. BC is a path based metric that evaluates the amount of influence of a node in the network (47). The BC of a node in graph  $G$  is expressed as:

$$BC = \sum_{i,j} \frac{g_{ij}}{n_i n_j} w_{ij}$$

where  $w_{ij}$  is the weight of the path between nodes  $i$  and  $j$ ,  $g_{ij}$  is the number of shortest paths between nodes  $i$  and  $j$ , and

$g_{ij} \ominus p_v$  is the number of shortest paths that pass through node  $v$  (not the  $v$  as end point). The same concept and equation are applicable for estimating the BC value of edges.



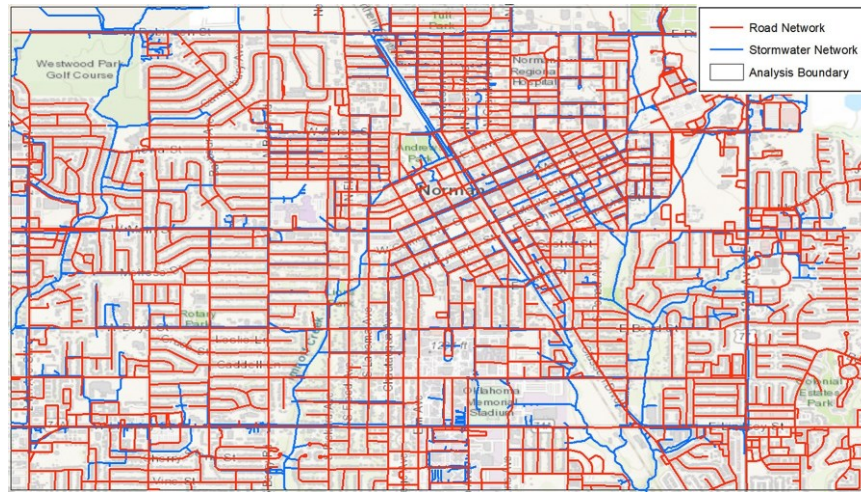


Figure 3. Road and stormwater networks inside the analysis boundary.

### Data Description

The road and stormwater networks of Norman, Cleveland County, Oklahoma are selected for this study for the following reasons: (i) the topology of the networks is known and (ii) high resolution network information is available. Figure 3 shows the map of road and stormwater networks within the analysis boundary (50). The data were collected from various sources, including state level organizations like Oklahoma Department of Transportation and Norman City open GIS portal websites (50, 51). The road network data includes high resolution network information, average annual daily traffic (AADT) data, 15-minute traffic count data, and clearly distinguishable intersections. However, this study considered only auto-based trips (AADT) while other modes including pedestrian, active transportation, transit, and so forth also contribute to traffic operations. Heavy rainfall leading to flash flooding in a road network tends to limit pedestrian activities, thus the functional aspects of a road network in this context are better understood by auto-based trips (52).

Because of discontinuities in the GIS data, the construction of a stormwater network requires additional filtration processes. Some of the local stormwater structures, such as culverts, were isolated from the original database and posed difficulties when all the components were combined. Additionally, some local pipelines and culverts provide immediate drainage of water from roads but are not a part of the stormwater network. Consideration of these isolated components would create incorrect mathematical formulation of the network. Such noise was thus removed from the GIS data for better representation of the network. This filtration process required careful observations and, out of 6,374 nodes, 1,637 (25.68%)

nodes were removed. Moreover, the stormwater network consists of a network of pipes at primary level that carries water to natural creeks and subsequently the water flows maintaining the hierarchy of channels. The GIS data considers the pipe network and natural systems separately, however, for this paper, both natural and pipe networks are combined into one shape file (Figure 3). Moreover, some of the links in the stormwater network were missing; these were difficult to see because they are buried underground. Based on a reconnaissance survey, some of the missing stormwater links were reconstructed. Finally, the pipe diameter was integrated in the hydrologic modeling (discussed in a later section) to obtain the direction and volume of water flow for a specific rainfall scenario. Network analysis is performed later to integrate these two vital pieces of information.

### Methods and Results Network

#### Representation

To evaluate the topological credentials of the road and stormwater systems, the GIS data is converted to a network or graph. Moreover, recent progress in computational power makes it possible to embed geographic coordinates information inside the graphs. For this paper, the shape files were converted to georeferenced graph files using relational database in R (53). Figures 4 and 5 illustrate the graph representation of the road ( $G_1$ ) and stormwater networks ( $G_2$ ), respectively. All the nodes and the edges are geotagged to keep the spatial reference embedded in the network.



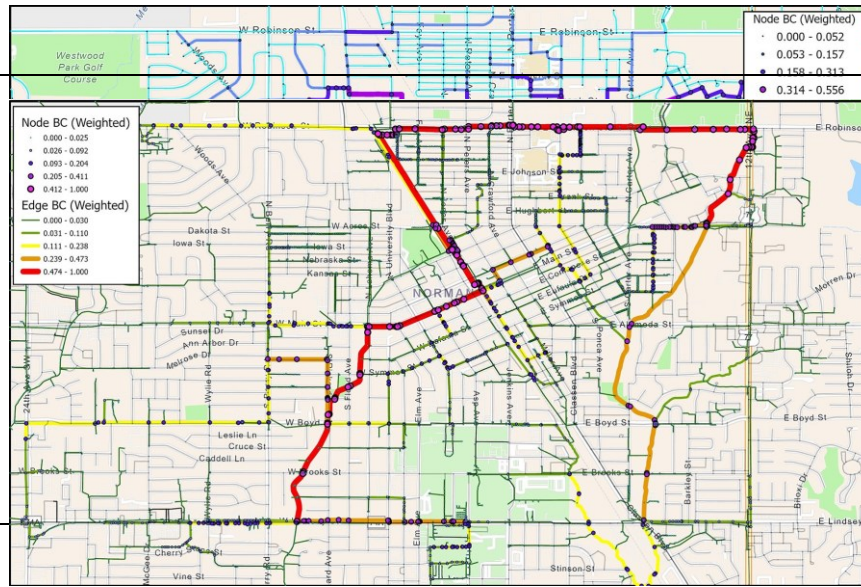


Figure 4. Graph representation of road network.

Figure 5. Graph representation of stormwater network.

**Nodes and Edges.** For the road network ( $G_1$ ), the intersections are defined as nodes and the road segments as edges. Using these criteria, the total number of nodes and edges in the road network were found to be 1,716 and 2,476, respectively. In the stormwater network ( $G_2$ ), inlets, manholes, and junctions of the pipelines are defined as nodes and the connections (conduits and creeks carrying stormwater) between the associated nodes as edges. The total number of nodes and edges were found to be 4,737 and 5,455, respectively.

**Directionality.** For this study,  $G_1$  and  $G_2$  are defined as undirected and weighted graphs and  $G_1'$  and  $G_2'$  are defined as directed and weighted graphs. Network analysis is performed for both directed and undirected graphs. Moreover,  $G_m$  and  $G_m'$  are defined as undirected and directed multilayer networks accordingly. In all cases the edges between  $G_1$  and  $G_2$  are bidirectional.



**Multilayer Graph.** The multilayer graph ( $G_m$ ) representation combines the stormwater and road networks and is developed based on spatial colocation between these networks (Figure 6). This relationship is established from spatial correlation analysis using global and local Moran's I values. Moreover, stormwater from highways drains to storm sewers through side drains, inlets, manholes, and so forth. Failure in stormwater conduits' capacity or other structural components results in standing water on the roadways which has an impact on traffic operations. Therefore, these two systems have functional interdependency. The multilayer network is developed in a way that captures both relationships between these systems. For

that overcome the challenge of connecting nodes at different elevations. Using ArcGIS Desktop (V10.8) (54) the spatial analyses are performed and the node indexes that satisfy the above criteria are identified. Finally, the inter- and intra-layer nodes and connectivity information are structured in the R environment using “tidygraph,” “igraph,” and “tidyverse” libraries and coded into the software muxViz (55– 57). This state-of-the-art software is developed in R library and has the capability to represent interdependent and connected multilayer networks.

After coding the  $G_1$ ,  $G_2$ ,  $G_1'$ ,  $G_2'$ ,  $G_m$ , and  $G_m'$  along with their weight, the graph properties are estimated, which are

Table 1. Network Properties

|                                                                                    | Unweighted and Undirected |                    |                    | Weighted and Undirected      |                    |                    |
|------------------------------------------------------------------------------------|---------------------------|--------------------|--------------------|------------------------------|--------------------|--------------------|
|                                                                                    | Road network              | Stormwater network | Multilayer network | Road network                 | Stormwater network | Multilayer network |
| Graph properties Nodes                                                             | 1,716                     | 4,737              | 6,454              | Same as for unweighted graph |                    |                    |
| Edges                                                                              | 2,476                     | 5,455              | 9,952              | Same as for unweighted graph |                    |                    |
| Diameter                                                                           | 68                        | 232                | 72                 | 10.64                        | 92.53              | 15                 |
| Density                                                                            | 0.00168                   | 0.00040            | 0.00048            | Same as for weighted graph   |                    |                    |
| Mean path length                                                                   | 25.54                     | 87.6               | 25.24              | 3.38                         | 33.95              | 3.78               |
| Node properties                                                                    |                           |                    |                    |                              |                    |                    |
| Average degree                                                                     | 2.89                      | 1.92               | 4.33               | 2.89                         | 1.92               | 4.33               |
| Eigenvector centrality<br>(number of nodes within<br>the threshold [.0.5/1]*)      | 11                        | 17                 | 4                  | 20                           | 20                 | 28                 |
| Node betweenness centrality<br>(number of nodes within<br>the threshold [.0.5/1]*) | 51                        | 156                | 41                 | 33                           | 116                | 23                 |
| Link property                                                                      | 64                        | 145                | 36                 | 55                           | 115                | 29                 |
| Edge betweenness centrality<br>(number of nodes within<br>the threshold [.0.5/1]*) |                           |                    |                    |                              |                    |                    |

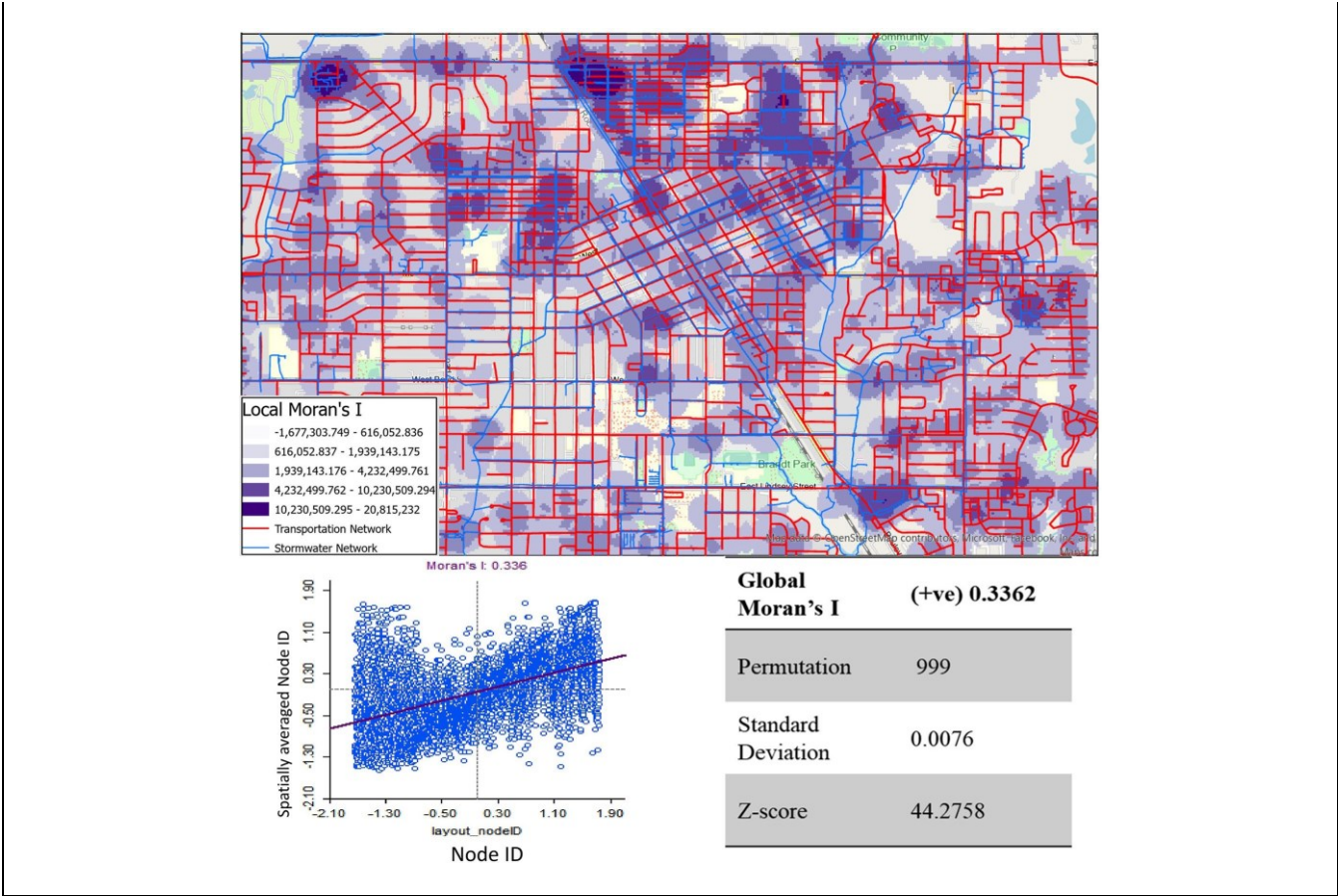
\*Note: Values are normalized between 0 to 1, where 0.5 is the threshold value and 1 is the highest value.

identifying the connectivity between  $G_1$  and  $G_2$ , it is assumed that nodes from the road and stormwater network within a sphere of 100 ft radius have a connection between them, and the interlayer edges are created based on this assumption (Figure 6). In our study area, most of the inlets are found to be near or at road intersections. As such, the study went through a rigorous trial-and-error method to obtain 100 ft radius distance that provides an optimal area where most water inlets at an intersection are included. Moreover, any radius greater than 100 ft resulted in problematic links or edges for the multilayered system, that is, water inlets located at one road intersection may end up connecting with another intersection. Instead of circles, spheres are used to capture the relationships

summarized in Table 1. After considering weight, the diameter of the graph is reduced, meaning more connectivity is observed. This is because the algorithm assigns 1 as the weight to all edges in unweighted analysis; however, an appropriate edge weight (normalized between 0 and 1) is assigned in weighted analysis which is less than 1 in most cases.

### Spatial Interdependency

To investigate the spatial interdependency of  $G_1$  and  $G_2$ , spatial autocorrelation with Moran's I statistics is used (58). Compared with other methods, Moran's I statistic is powerful because it can capture both global and local



spatial autocorrelation, and so it has become the well-established model for expressing spatial autocorrelation (59, 60). In this analysis, both local and global Moran's I values are reported for identifying neighbors in different spaces (61). The global Moran's I represents the overall clustering of any variable in the space using spatial weighting (rook/queen contiguity and orders) and averaged variables, expressed as:

$$I_{global} = \frac{\sum_i \sum_j w_{ij} \bar{x}_i \bar{x}_j}{\sum_i \sum_j w_{ij} \bar{x}_i^2}$$

where N is the number of observations,  $\bar{x}$  is the mean of the variable,  $w$  is spatial weight, and  $W$  is the sum of all spatial weights. The inference of Moran's I statistics is based on the null hypothesis of complete randomness in space, that is, no pattern of autocorrelation. The value of  $I$  ranges from -1 to 1, where 1 means perfect cluster together, 0 is complete randomness of clusters, and -1

Figure 7. Spatial autocorrelation between  $G_1$  and  $G_2$ .

means perfectly dispersed. However, global  $I$  value gives one statistic for both networks considering the global homogeneity of nodes whereas some local clusters may be present in space. The concept of local Moran's I statistic is useful to capture this scenario. The local Moran's I statistic calculates individual spatial units separately and identifies the significance over space, expressed as:

$$I_{local} = \frac{\sum_j w_{ij} \bar{x}_i \bar{x}_j}{\sum_j w_{ij} \bar{x}_i^2}$$

where the symbols represent the same meaning as in Equation 8. The global measure of Moran's I for the roads and stormwater networks is +0.3362, this means that the nodes of the road and stormwater networks are clustered in space. The recorded Z-score is 44.276 which shows that the result is significant. Figure 7 shows Moran's I scatter plot with high-high (top-right quadrant), low-low (bottom-left quadrant) clustering regions, which is visualized in the local cluster map. The global Moran's I value and the Z-score provide evidence of spatial clustering of nodes from transportation and stormwater networks which affirm the presence of spatial interdependency between them.



Likewise local Moran's I values indicate local clustering and, based on this spatial correlation between nodes from the said networks, a multilayer network is constructed. Moreover, the local Moran's I gives a spatial context to assign weight to spatially interdependent edges of  $G_m$ . This study considers local Moran's I value (normalized) as a spatial weight for multilayer network analysis.

## Complex Network Analysis

**Degree and Degree Distribution.** The degrees of  $G_1$ ,  $G_2$ , and  $G_m$  are estimated using Equations 1 and 2. For this analysis, an undirected network is considered, which means the degrees shown in Figures 8 and 9 are the sum of all in-degree and out-degree. After the analysis, the highest degrees for  $G_1$ ,  $G_2$ , and  $G_m$  are found to be 5, 7, and 28, respectively. This means that some of the nodes in the multilayer network are highly connected compared with the individual networks. The distribution of node degree is presented in Figure 8, which shows a long tail right skewed power law distribution for all three networks.

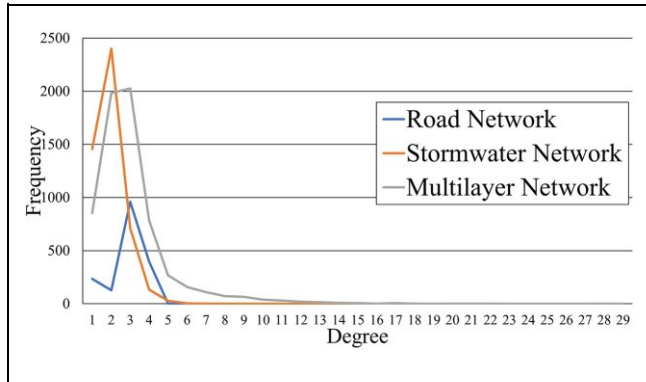


Figure 8. Degree distribution of  $G_1$ ,  $G_2$ , and  $G_m$ .

This implies the presence of nodes with very high degree values, meaning the presence of hubs with high connectivity. This power distribution is the property of realworld networks and the graph developed for the three networks resembles this property (62). In addition,  $G_m$  has three nodes with higher degree compared with  $G_1$  and  $G_2$  as it connects both layers with hypothetical interlayer edges. These interlayer edges represent the spatial dependency attribute between the two layers; the development and definition of these edges are significant contributions of this study. Table 1 shows that the average degree of  $G_m$  is 4.33, which is significantly higher than  $G_1$  (2.89) and  $G_2$  (1.92). The nodes with degree values of  $G_1$ ,  $G_2$ , and  $G_m$  are illustrated in the map (Figure 9, a–c). Most of the nodes (intersections) in the road network with higher degrees are identified around the local roads (“Alameda St” at the

roundabout [degree = 5], “Santa Fe Ave,” “Miller Ave,” “Main St,” and “24<sup>th</sup> Ave”). For the stormwater network, the nodes with highest degree values are found near the residential areas (near “Boyed St” and “Flood Ave,” “Main St” and “Ponca Ave,” “Classen Blvd” and “Lindsey St”). For the multilayer network, the nodes with higher degree values are found near the residential areas while some of them are close to creeks (“Cater Ave” and “Apache St,” “Robinson St” and “Fay Ave,” “Iowa St” and “Berry Ave,” “Boyed St” and “Jenkins Ave”). The degree of a node represents varied fundamental properties in a network. Other network properties, for example, centrality, are highly dependent on the degree of a node. The changing pattern of topological credentials based on node degree identifies the significant influence of the built environment, as higher degree nodes are found near residential areas.

**Eigenvector Centrality (EC).** Equation 7 is used to estimate the weighted EC for undirected networks  $G_1$ ,  $G_2$ , and  $G_m$  (normalized between 0 and 1). For this analysis  $G_1$  and  $G_2$  are assigned AADT and conduit capacity as weight, respectively. In addition, Moran's I significance value is assigned as weight to the nodes with interlayer connectivity. It is found that both  $G_1$  and  $G_2$  have 20 nodes with EC values above the threshold (0.5/1), (where 0.5 is the threshold value and 1 the largest value, denoted as 0.5/1). Similarly,  $G_m$  has 28 nodes with the highest EC value within same threshold (0.5/1). As the node degree distributions of all three networks are right skewed long tail power distribution, the EC values are also expected to follow the same property trend. This result shows the presence of very few nodes with high EC values (1.2% for  $G_1$ , 0.4% for  $G_2$ , and 0.4% for  $G_m$ ), which follows the same characteristics as degree. The nodes with highest EC values are also found to be spatially clustered for all three networks (Figure 10, a–c) but the clusters are not in the same places. For  $G_1$  the nodes are clustered near “Cleveland Elementary School”; for  $G_2$  the nodes are clustered between “Main St” and “Porter Ave”; but for  $G_m$  the nodes are near “Carter Ave” and “Comanche St.” This seems logical since many of the stormwater nodes are located in neighboring locations and connect to “Bishop Creek.” EC in  $G_m$  is also estimated based on the combination of  $G_1$ ,  $G_2$ , and their interlayer connections, so the influential nodes have shifted to some other places. In other words, highly influential nodes in a multilayer network that dictate the intra- and inter-connectivity are not the same as in individual systems, rather the properties are changed and new central locations identified. Figure 10, a–c, shows the classification of nodes based on EC values for  $G_1$ ,  $G_2$ , and  $G_m$ .

**Node Betweenness Centrality (BC).** Weighted BCs (normalized between 0 and 1) of nodes for undirected

networks  $G_1$ ,  $G_2$ , and  $G_m$  are estimated using Equation 7 where the weights are considered same as in the previous analysis. The result reveals that  $G_1$  has 33 nodes and  $G_2$  has 116 nodes within the threshold of  $[.0.5/1]$ . The same analysis is performed on the  $G_m$  and only 23 nodes were found within the higher BC value threshold  $[.0.5/1]$ . This means that BC value changes significantly from individual network to multilayer network. The nodes with classified BC values of networks  $G_1$ ,  $G_2$ , and  $G_m$  are shown in Figure 11, a–c. It is identified that the most central nodes in the road network are found near “Eufaula St” and “Jones Ave”; some are scattered near “College Ave,” “Elm Ave,” and “Barley St.” Since intersections in local roads provide connectivity to roads with higher AADT, the local roads are more central in the analysis area. On the contrary, the highest central nodes in  $G_2$  are found near “Main St” and “Legacy Trails,” which is logical as many stormwater conduits connect in this location. For  $G_m$ , the locations are close to that of  $G_1$  and  $G_2$  (“Eufaula St” and “Main St”) and this seems rational since nodes with higher BC values in individual networks are located nearby. In general, BC is an important shortest path

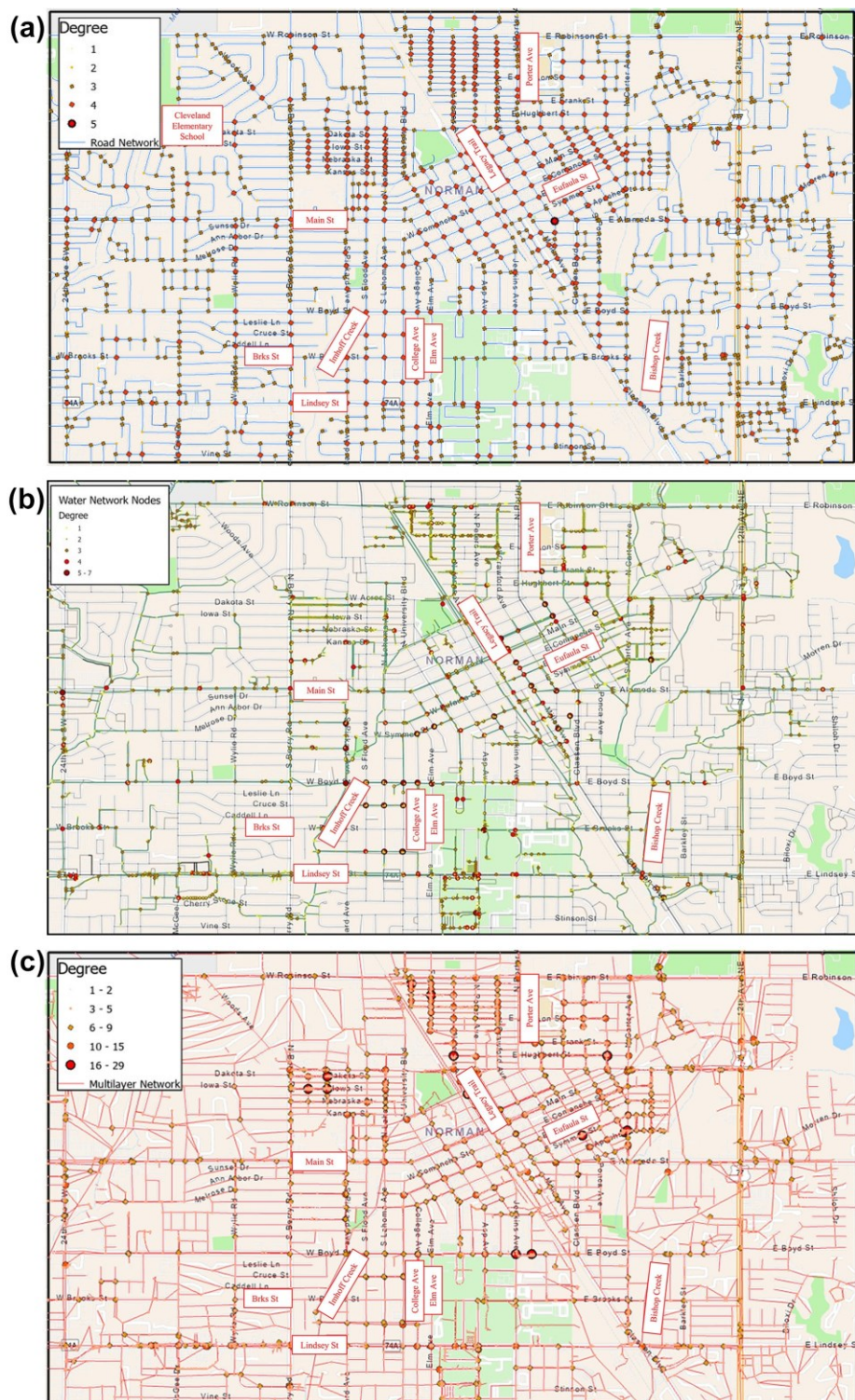


Figure 9. Degrees of nodes in: (a) road network ( $G_1$ ), (b) stormwater network ( $G_2$ ), and (c) multilayer network ( $G_m$ ).







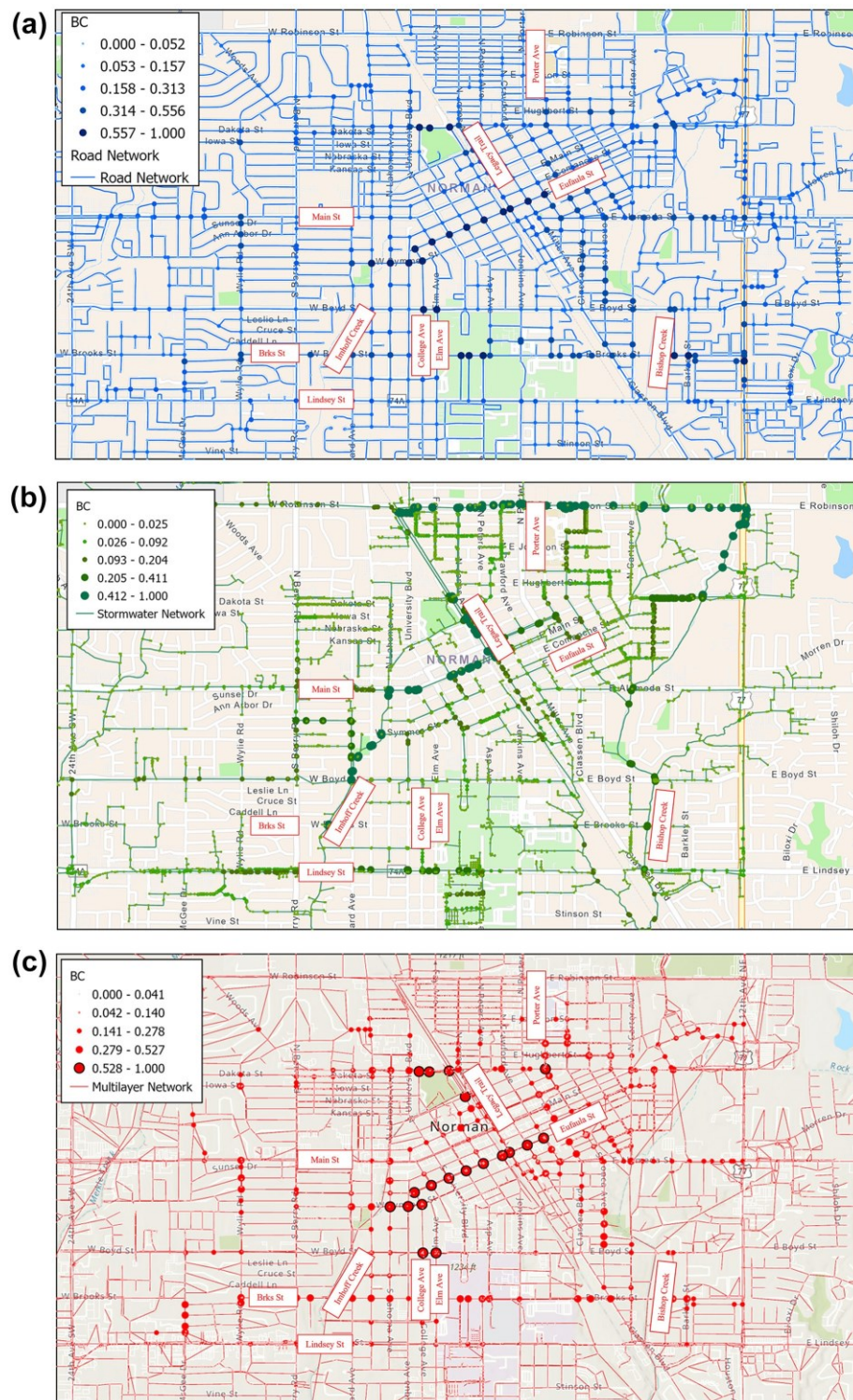


Figure 11. Locations of central nodes of: (a) road network ( $G_1$ ), (b) stormwater network ( $G_2$ ), and (c) multilayer network ( $G_m$ ), based on betweenness centrality (BC) value.

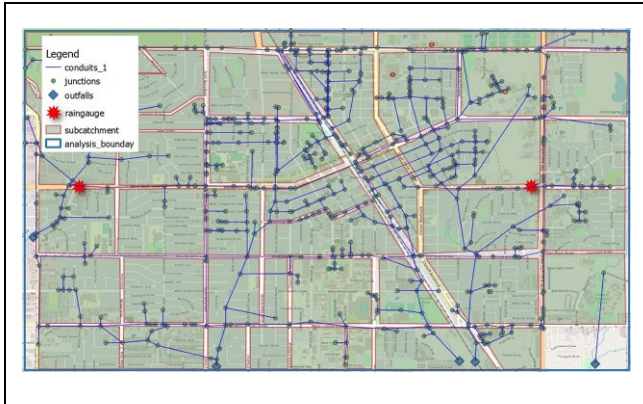


Figure 12. Hydrologic analysis of the study area.

based metric used for network traffic pattern analysis (63) and water distribution system analysis (64), and the same metric makes an important contribution to multilayer network analysis (64).

**Hydrologic Analysis.** Hydrologic analysis of the storm water system is performed to reveal the direction and the volume of the water flow in the study area, which provides information about direction of edges in the stormwater network. The edge BC of the directed stormwater network in the following section utilizes such information to perform and obtain realistic results. The stormwater in the study area flows by gravity, firstly from the roads to the storm sewers and finally inside the storm sewer network. To perform the hydrologic analysis, the area is divided into several sub-catchment zones and a sample precipitation (minimum 2.5in. per hour to maximum 7.5in. per hour) is assigned to observe the direction of the water flow. The elevations of junctions, inlets, and manholes are estimated from the digital elevation map of Norman, Oklahoma (65). Additionally, the creeks in the study area are treated as part of the stormwater pipe network. The overall outfalls for water to go out of the area are considered as the end points of the creeks (Figure 12). The hydrologic simulation performed in the Storm Water Management Model (SWMM), software from the U.S. Environmental Protection Agency, gives the direction and volume of water flow in the pipe network (66). Based on this, the directed stormwater network ( $G_2'$ ) is defined and the volume of water flow in the pipes is considered as a weighting factor for network analysis.

**Edge Betweenness Centrality (BC).** Edge BC is another important shortest path based network measure that identifies how central an edge is in the network. For this analysis, Equation 7 is used to estimate the weighted and undirected

BC (normalized between 0 and 1) of  $G_1$ ,  $G_2$ , and  $G_m$ . The weights used for this analysis are the same as in the previous analysis; the only difference is that weights are assigned to the edges instead of nodes. Individual layer BC values with classification are shown in Figure 13, a, d. For  $G_1$  the most central edges are located near “College Ave,” “Lindsey St,” and “Eufaula St.” Being parts of local roads, these central road segments provide more connectivity than arterial roads. Similarly, some central edges of  $G_2$  follow parts of the creeks and others are in the pipe network. To be more specific, for  $G_1$  and  $G_2$  a total of 55 and 115 edges, respectively, are found within the BC threshold above 0.5 in a scale of 0 to 1. Similarly, 29 edges are found to be central for  $G_m$  for the same BC threshold [0.5/1]. This result exhibits the changed topology of the multilayer network and identifies edges that are important for the combined network as opposed to results from analysis of individual networks. This means that multilayer network indicates to locations where road and stormwater networks are mutually central (critical). Any disruption in these central locations may create cascading failures that propagate from one network to another. Figure 13, a, c, and e, show the locations of edges with centrality values (darker and thicker lines have higher centrality) for  $G_1$ ,  $G_2$ , and  $G_m$ . It is also identified that all the edges with high BC are close to locations which are vulnerable to cascading failure (for  $G_1$  “Eufaula St” and “Barkley St,” for  $G_2$  near “Main St” and “Legacy Trail,” and for  $G_m$  around “Eufaula St,” “Main St,” and “Legacy trail”).

**Directed Network Analysis.** For analysis of the directed networks, edges of the road, stormwater, and multilayer networks are expressed with direction and introduced as  $G_1'$ ,  $G_2'$ , and  $G_m'$ . For the road network ( $G_1'$ ), traffic flow direction is considered as the direction of flow in the edges. In the study area, most of the roads are bidirectional except for a few links, so the network is cyclic, that is, there are more than one path to navigate between nodes. For the stormwater network, the direction of edges is considered based on direction of water flow, which is identified from hydrologic analysis. This network has acyclic tree structure, that is, the presence of hierarchy of edges, and water flows from lower to higher ranked elements based on gravity. This is a more realistic representation of the physical system, as water cannot flow backward in the directed network.

The interdependent multilayer ( $G_m'$ ) network is also considered as a directed network, where the individual layers' edge direction remains the same as before and interlayer links are represented as bidirectional edges. This is links representation of the direction as failures (or vulnerability) between the two systems is assumed to cascade through the



interlayer edges. Being interdependent, failures may propagate between road

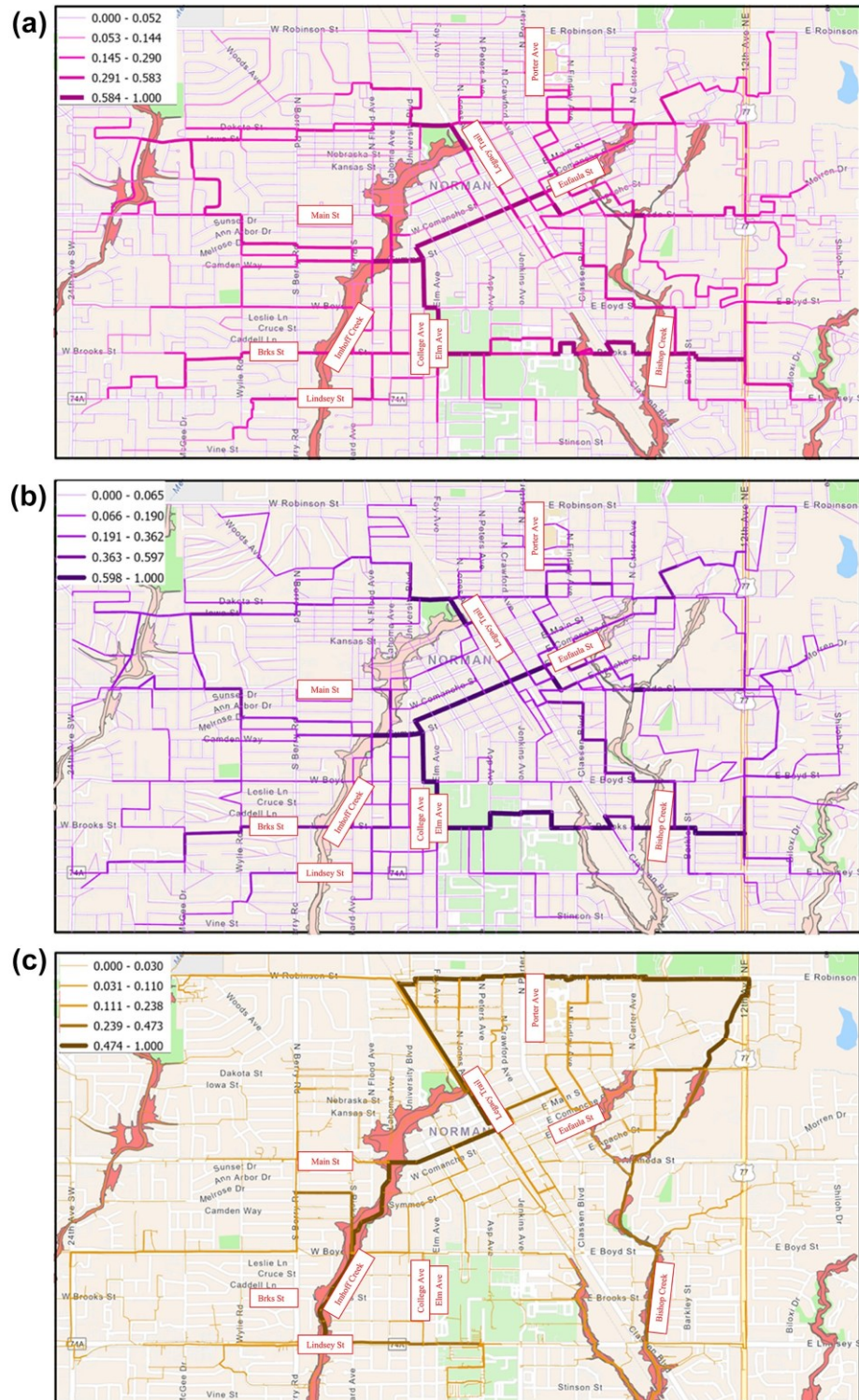


Figure 13. (Continued)

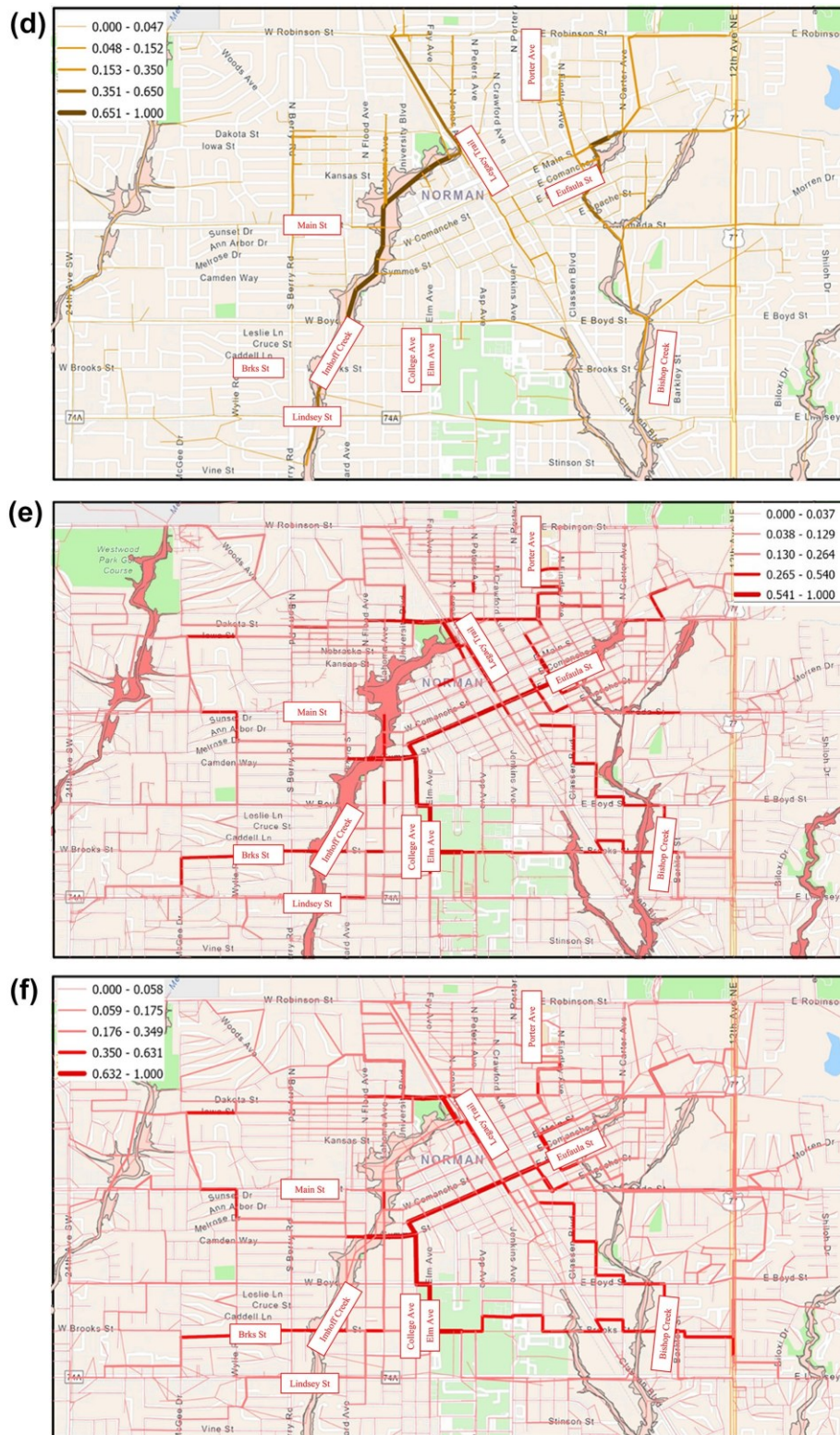


Figure 13. Locations of central edges of: (a) undirected road network ( $G_1$ ), (b) directed road network ( $G_1'$ ), (c) undirected stormwater network ( $G_2$ ), (d) directed stormwater network ( $G_2'$ ), (e) undirected multilayer network ( $G_m$ ), and (f) directed multilayer network ( $G_m'$ ) based on betweenness centrality (BC) value.



and stormwater networks. Other than direction of flow, all weights of the network components are considered same as  $G_m$ .

The road network is analyzed for both directed and undirected cases, but no significant difference in BC of edges is observed because the network structure is cyclic and almost all the roads are bidirectional (Figure 13, a and b). This study considers both local and arterial streets, where a small part of “West Main St” (an arterial road) has one-directional flow. Additionally, a few of the local roads are in one-way operation, so the network analysis shows similar results for both networks ( $G_1$  and  $G_1'$ ). Parts of “Brks St” and “Eufaula St” are identified as central in the road network. It is also observed that edges having similar BC exhibit high spatial correlation (clustering) which is a good predictor of traffic patterns (63).

On the other hand, water flow in the stormwater network is different than traffic flow, in that water flows in one direction in each edge. The flow starts from inlets, then follows conduits based on elevation and finally reaches the creeks. A hierarchy of components is observed in this network. This observation leads to significantly different results in unidirectional and directional analysis. While the pipes connected to secondary stormwater conduits and a small part of natural creeks are found to be central in undirected analysis, the natural creeks are identified as central in directed network analysis (Figure 13, c and d). In practice, this is the expected result. By interpreting the flood hazard map of Norman, Oklahoma (data collected from FEMA), the creeks are identified as potential flood hazard zones too (67). Therefore, the directional analysis of edge BC can express the criticality of stormwater components for flooding in the study area.

The central edges based on edge BC values in the multilayer network ( $G_m'$ ) are illustrated in (Figures 13, e and f). Compared with analysis of undirected networks, more specific spatial clusters of central locations are observed in the multilayer network when directed network analysis is performed. This phenomenon is observed in real networks, as discussed earlier (63). The multilayer network ( $G_m'$ ) identifies the edges with high centrality as near “Brks St,” “Elm Ave,” and “Eufaula St,” which are also close to those identified by individual road and stormwater network analysis.

## Conclusions

The analytical framework developed in this study uncovers a unique approach to represent two physical systems, that is, the road and the stormwater networks in a multilayer network structure. In addition to that, global Moran's I is used as an indicator to quantify the spatial interdependency

between the two networks. Moreover, weight is assigned to networks (i.e., AADT as functional weight of road network, conduit capacity as weight of the stormwater network, and local Moran's I significance value as spatial weight to interlayer edges) to capture the functional and spatial relationships. The topological credentials of road, stormwater, and multilayer networks are thus estimated. Finally, the analysis framework captures the metrics for interdependency study. Overall, this analytical approach to investigate two systems gives an understanding about the applicability of multilayer approach for spatial and functional relationships in addition to connectivity between networks. Additionally, the critical locations and components identified by multilayer network and individual networks spatially coincide with actual flood hazard zones, which shows the credibility of network metrics to identify critical locations. The detailed analysis in this paper provides the following key insights:

Spatial autocorrelation estimated by global Moran's I is a good indicator of spatial interdependence. Moreover, spatial weight (assigned to links or edges between road and stormwater networks) generated from local Moran's I produces logical estimates of topological credentials.

Most of the central road segments (based on BC) are identified as local roads whereas the study includes local, collector, and arterial roads. In a city area, local roads are more connected and produce higher degree nodes and central edges compared with less connected arterial roads.

Most of the central edges (based on BC) of the stormwater network are found along the creeks. The directed and weighted network analyses capture the real representation of the stormwater network while the undirected analysis cannot identify the hierarchy of water flow properly.

EC estimates the most influential nodes in the network and this study found that the nodes with high EC are spatially clustered near nodes with high degree. The locations are not the same for stormwater, road, and multilayer networks, however. EC indicates the node's importance by its neighboring nodes. However, EC cannot capture path influence in an individual or multilayer network. Therefore, EC can be used to capture node influence (intersections/manholes/ junction) for vulnerability analysis.

The directed network analyses of road, stormwater, and multilayer networks show that edges with high BC are spatially close to each other. Undirected network analysis cannot capture this

phenomenon (i.e., for multilayer network, the edges with similar centrality are more scattered).

For the multilayer network, most central nodes and edges are found in proximity to those of stormwater and road networks (BC).

Topological credentials (degree and BC) also indicate the criticality of the similar nodes and edges. One of challenges of studying the “interdependency of systems” is to identify locations vulnerable to cascading failure. This study indicates that the topological credentials of a multilayer network have the ability to indicate critical components and locations vulnerable to cascading failure. For example, if a road segment is flooded in the north-western part of the study area because of the capacity failure of a stormwater pipe, the failure is less severe than if the same phenomenon were to happen near “Elm Ave” or “Eufaula St.” The effect of cascading and escalating of failure is higher near the more central edges.

Based on the results of the analysis, this study offers the following recommendations for the future interdependency modeling. Networks’ topological credentials have the potential to contribute to modeling of systems’ interdependency, especially when the systems are physical and have spatial as well as operational relationships. Moreover, a network-based modeling approach should consider multilayer network representation of the combined systems which is more credible than single layer network analysis. This study also suggests that directed network analysis captures the real physical system better than undirected analysis, so future analysis should not ignore the directionality aspect of networks. Since spatial autocorrelation analysis can capture spatial dependencies between systems, vulnerability analysis should include this geographical relationship of networks as a metric for better understanding of systems.

This study was limited by some assumptions which were made for simplicity of analysis. It was approximated by trial-and-error method that nodes of road and stormwater networks need to be within a 100 ft radius sphere to define the spatial interdependency between them. Additionally the scaling effect, which is an important property of network analysis (17), is not captured in this study. For example, some natural creeks close to the boundary of the study area have lower ranking (based on EC and BC) whereas these channels are an important part of the overall stormwater system. This scenario would be captured if the analysis were performed on a bigger scale. Moreover, the study is conducted for a specific location (i.e., Norman, Oklahoma) which limits the validation process. AADT for the road network and water flow volume for the stormwater network are considered as functional components for the analysis framework. Instead of one, a set of functional

components (e.g., AADT, speed, flow for road network) may better represent the overall functionality of the system. Moreover, real-time stormwater flow measurement can be integrated into the framework as a weighting factor for the network analysis. It is not proven if the analysis is free of ecological fallacy as the spatial analysis is performed based on the data within the boundary. While on a macro scale, there is logical interdependency between the road and stormwater networks, for example, runoff management, changed land use pattern, maintenance and repair works indirectly affect both systems, this study was confined to direct special and functional relationships only. This study also considered that the spatial interdependency of networks is at the node level, while the relationship can be edge-to-edge. As the inlets and manholes from stormwater networks are mostly found at or near road intersections, this consideration simplifies the analysis framework by connecting the nodes from these networks. Also, this study captures the properties and phenomenon at the node, inside edge failures cannot be captured until they reach the nodes. However, this limitation can be overcome by using dual representation of graph (68).

To overcome these limitations, as well as based on the facts and evidence explored in this study, some future directions of research are identified. The analytical framework developed in this study will be used to investigate cascading failure between the networks using real flood scenarios. While the proposed research approach provides new insights into the understanding of how critically road networks depend on stormwater systems, it would benefit future research to utilize the findings of this study in testing different disruption scenarios caused by flooding (i.e., removing a section of Interstate would have less impact than removing an arterial or collector road that runs parallel to it, making the situation much more catastrophic) at different geographic scales, landscape and topography (i.e., rural versus urban; city versus county; grid versus radial road patterns; high elevation versus elevation differences). Furthermore, the scaling effect can be addressed by investigation of the topological credentials for multilayer networks of more than two systems. Sensitivity and elasticity analysis of graph metrics from different case studies will validate the modeling framework. While this study analyzed four centralities, other metrics, like closeness centrality or PageRank centrality can be tested to identify the most important topological credentials that capture the interdependency between the systems. A timely research need is to develop a calibrated and validated modeling framework to address the behavior of a “system of systems” using complex network science. Finally integrating atop level modeling approach, for example, ABM, in the framework may help to interpret better the interdependency of systems.

### Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: H. M. I. Kays, A. M. Sadri, K. K. Muraleetharan, P. S. Harvey, G. A. Miller; data collection: H. M. I. Kays, A. M. Sadri, K. K. Muraleetharan, P. S. Harvey, G. A. Miller; data analysis and interpretation: H. M. I. Kays, A. M. Sadri, K. K. Muraleetharan, P. S. Harvey, G. A. Miller; draft manuscript preparation: H. M. I. Kays, A. M. Sadri, K. K. Muraleetharan, P. S. Harvey, G. A. Miller. All authors reviewed the findings and approved the final manuscript version.

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### ORCID iDs

H. M. Imran Kays  <https://orcid.org/0000-0001-9093-5114>  
 Arif Mohaimin Sadri  <https://orcid.org/0000-0001-5571-6741>

K.K. “Muralee” Muraleetharan  <https://orcid.org/0000-0002-4187-4818>

P. Scott Harvey  <https://orcid.org/0000-0002-0565-3102>  
 Gerald A. Miller <https://orcid.org/0000-0001-6460-1030>

### References

1. Critical Infrastructure Sectors | CISA. <https://www.cisa.gov/critical-infrastructure-sectors>. Accessed March 12, 2022.
2. Rahimi-Golkhandan, A., B. Aslani, and S. Mohebbi. Predictive Resilience of Interdependent Water and Transportation Infrastructures: A Sociotechnical Approach. *SocioEconomic Planning Sciences*, Vol. 80, 2022, p. 101166.
3. Rinaldi, S. M., J. P. Peerenboom, and T. K. Kelly. Identifying, Understanding, and Analyzing Critical Infrastructure Interdependencies. *IEEE Control Systems Magazine*, Vol. 21, No. 6, 2001, pp. 11–25.
4. Sun, W., P. Bocchini, and B. D. Davison. Overview of Interdependency Models of Critical Infrastructure for Resilience Assessment. *Natural Hazards Review*, Vol. 23, No. 1, 2022, p. 04021058.
5. Zimmerman, R. Decision-Making and the Vulnerability of Interdependent Critical Infrastructure. 2004 IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat No04CH37583), The Hague, The Netherlands, IEEE, New York, NY, 2004, pp. 4059–4063.
6. Zhang, P., and S. Peeta. A Generalized Modeling Framework to Analyze Interdependencies Among Infrastructure Systems. *Transportation Research Part B: Methodological*, Vol. 45, No. 3, 2011, pp. 553–579.
7. Bin Wee, X., M. Herrera, G. M. Hadjidemetriou, and A. Kumar Parlikad. Simulation and Criticality Assessment of Urban Rail and Interdependent Infrastructure Networks. *Transportation Research Record*, 2022. 2677(1): 1181–1196.
8. Kays, H. M., and A. M. Sadri. Toward Unifying Resilience and Sustainability for Transportation Infrastructure Systems: Conceptual Framework, Critical Indicators, and Research Needs (No. TRBAM-22-04025). 2022.
9. Dimitriou, D., and M. Sartzetaki. Assessment of Socioeconomic Impact Diversification from Transport Infrastructure Projects: The Case of a New Regional Airport. *Transportation Research Record*, 2022. 2676(4): 732–745.
10. Li, Z., W. Tang, X. Lian, X. Chen, W. Zhang, and T. Qian. A Resilience-Oriented Two-Stage Recovery Method for Power Distribution System Considering Transportation Network. *International Journal of Electrical Power & Energy Systems*, Vol. 135, 2022, p. 107497.
11. Schmitt, T. G., and C. Scheid. Evaluation and Communication of Pluvial Flood Risks in Urban Areas. *WIREs Water*, Vol. 7, No. 1, 2020, p. e1401.
12. Araya, F., and S. Vasquez. Challenges, Drivers, and Benefits to Integrated Infrastructure Management of Water, Wastewater, Stormwater and Transportation Systems. *Sustainable Cities and Society*, Vol. 82, 2022, p. 103913.
13. Hoang, L., and R. A. Fenner. System Interactions of Stormwater Management Using Sustainable Urban Drainage Systems and Green Infrastructure. *Urban Water Journal*, Vol. 13, No. 7, 2016, pp. 739–758.
14. Carr, R. W., and S. G. Walesh. Micromanagement of Stormwater in a Combined Sewer Community for Wet Weather Control – The Skokie Experience. 11th International Conference on Urban Drainage, Edinburgh, UK, 2008.
15. Ouyang, M. Review on Modeling and Simulation of Interdependent Critical Infrastructure Systems. *Reliability Engineering & System Safety*, Vol. 121, 2014, pp. 43–60.
16. Hasan, S., and G. Foliente. Modeling Infrastructure System Interdependencies and Socioeconomic Impacts of Failure in Extreme Events: Emerging R&D Challenges. *Natural Hazards*, Vol. 78, No. 3, 2015, pp. 2143–2168.
17. Ahmed, M. A., A. M. Sadri, A. Mehrabi, and A. Azizinamini. Identifying Topological Credentials of Physical Infrastructure Components to Enhance Transportation Network Resilience: Case of Florida Bridges. *Journal of Transportation Engineering, Part A: Systems*, Vol. 148, No. 9, 2022, p. 04022055.
18. Newman, M. *Networks: An Introduction*. Oxford University Press, Oxford, 2010.
19. De Domenico, M., A. Sole’-Ribalta, E. Cozzo, M. Kivela, Y. Moreno, M. A. Porter, S. Go’mez, and A. Arenas. Mathematical Formulation of Multilayer Networks. *Physical Review X*, Vol. 3, No. 4, 2013, p. 041022.
20. Pederson, P., D. Dudenhoefter, S. Hartley, and M. Permann. Critical Infrastructure Interdependency Modeling: A Survey of US and International Research. *Idaho National Laboratory*, Vol. 25, 2006, p. 27.



21. Sharkey, T. C., S. G. Nurre, H. Nguyen, J. H. Chow, J. E. Mitchell, and W. A. Wallace. Identification and Classification of Restoration Interdependencies in the Wake of Hurricane Sandy. *Journal of Infrastructure Systems*, Vol. 22, No. 1, 2016, p. 04015007.
22. Rathnayaka, B., C. Siriwardana, D. Robert, D. Amaratunga, and S. Setunge. Improving the Resilience of Critical Infrastructures: Evidence-Based Insights from a Systematic Literature Review. *International Journal of Disaster Risk Reduction*, Vol. 78, 2022, p. 103123.
23. Sathurshan, M., A. Saja, J. Thamboo, M. Haraguchi, and S. Navaratnam. Resilience of Critical Infrastructure Systems: A Systematic Literature Review of Measurement Frameworks. *Infrastructures*, Vol. 7, No. 5, 2022, p. 67.
24. De Felice, F., I. Baffo, and A. Petrillo. Critical Infrastructures Overview: Past, Present and Future. *Sustainability*, Vol. 14, No. 4, 2022, p. 2233.
25. Liu, W., M. Shan, S. Zhang, X. Zhao, and Z. Zhai. Resilience in Infrastructure Systems: A Comprehensive Review. *Buildings*, Vol. 12, No. 6, 2022, p. 759.
26. McDaniels, T., S. Chang, K. Peterson, J. Mikawoz, and D. Reed. Empirical Framework for Characterizing Infrastructure Failure Interdependencies. *Journal of Infrastructure Systems*, Vol. 13, No. 3, 2007, pp. 175–184.
27. Aghababaei, M., and M. Koliou. An Agent-Based Modeling Approach for Community Resilience Assessment Accounting for System Interdependencies: Application on Education System. *Engineering Structures*, Vol. 255, 2022, p. 113889.
28. Oliva, G., S. Panzieri, and R. Setola. Agent-Based Input–Output Interdependency Model. *International Journal of Critical Infrastructure Protection*, Vol. 3, No. 2, 2010, pp. 76–82.
29. Johansson, J., and H. Hassel. An Approach for Modelling Interdependent Infrastructures in the Context of Vulnerability Analysis. *Reliability Engineering & System Safety*, Vol. 95, No. 12, 2010, pp. 1335–1344.
30. Wang, S., L. Hong, and X. Chen. Vulnerability Analysis of Interdependent Infrastructure Systems: A Methodological Framework. *Physica A: Statistical Mechanics and its Applications*, Vol. 391, No. 11, 2012, pp. 3323–3335.
31. Chai, C. L., X. Liu, W. J. Zhang, and Z. Baber. Application of Social Network Theory to Prioritizing Oil & Gas Industries Protection in a Networked Critical Infrastructure System. *Journal of Loss Prevention in the Process Industries*, Vol. 24, No. 5, 2011, pp. 688–694.
32. Sharma, N., and P. Gardoni. Mathematical Modeling of Interdependent Infrastructure: An Object-Oriented Approach for Generalized Network-System Analysis. *Reliability Engineering & System Safety*, Vol. 217, 2022, p. 108042.
33. Abdel-Mottaleb, N., and Q. Zhang. Water Distribution–Transportation Interface Connectivity Responding to Urban Geospatial Morphology. *Journal of Infrastructure Systems*, Vol. 26, No. 3, 2020, p. 04020025.
34. Dong, S., H. Wang, A. Mostafizi, and X. Song. A Network-of-Networks Percolation Analysis of Cascading Failures in Spatially Co-Located Road-Sewer Infrastructure Networks. *Physica A: Statistical Mechanics and its Applications*, Vol. 538, 2020, p. 122971.
35. Dong, S., T. Yu, H. Farahmand, and A. Mostafavi. Probabilistic Modeling of Cascading Failure Risk in Interdependent Channel and Road Networks in Urban Flooding. *Sustainable Cities and Society*, Vol. 62, 2020, p. 102398.
36. Dong, S., X. Gao, A. Mostafavi, and J. Gao. Modest Flooding Can Trigger Catastrophic Road Network Collapse Due to Compound Failure. *Communications Earth and Environment*, Vol. 3, No. 1, 2022, pp. 1–10.
37. Atef, A., and O. Moselhi. Modeling Spatial and Functional Interdependencies of Civil Infrastructure Networks. In *Pipelines 2014: From Underground to the Forefront of Innovation and Sustainability*, pp. 1558–1567.
38. Aslani, B., and S. Mohebbi. Data on Predictive Resilience of Interdependent Water and Transportation Infrastructures: A Sociotechnical Approach. *Data in Brief*, Vol. 39, 2021, pp. 107512.
39. Mazumder, R. K., A. M. Salman, Y. Li, and X. Yu. Asset Management Decision Support Model for Water Distribution Systems: Impact of Water Pipe Failure on Road and Water Networks. *Journal of Water Resources Planning and Management*, Vol. 147, No. 5, 2021, p. 04021022.
40. Newman, M. E. The Structure and Function of Complex Networks. *SIAM Review*, Vol. 45, No. 2, 2003, pp. 167–256.
41. Kinsley, A. C., G. Rossi, M. J. Silk, and K. Vander Waal. Multilayer and Multiplex Networks: An Introduction to Their Use in Veterinary Epidemiology. *Frontiers in Veterinary Science*, Vol. 7, 2020, p. 596.
42. Bashan, A., Y. Berezin, S. V. Buldyrev, and S. Havlin. The Extreme Vulnerability of Interdependent Spatially Embedded Networks. *Nature Physics*, Vol. 9, No. 10, 2013, pp. 667–672.
43. Sadri, A. M., S. V. Ukkusuri, and H. Gladwin. Modeling Joint Evacuation Decisions in Social Networks: The Case of Hurricane Sandy. *Journal of Choice Modelling*, Vol. 25, 2017, pp. 50–60.
44. De Domenico, M. Multilayer Networks: Analysis and Visualization. *Introduction to muxViz with R*. Springer, Cham, 2022.
45. Sadri, A. M., S. Hasan, S. V. Ukkusuri, and M. Cebrian. Exploring Network Properties of Social Media Interactions and Activities During Hurricane Sandy. *Transportation Research Interdisciplinary Perspectives*, Vol. 6, 2020, p. 100143.
46. Yang, S. Networks: An Introduction by M. E. J. Newman. *The Journal of Mathematical Sociology*, Vol. 37, No. 4, 2013, pp. 250–251.
47. Malek, M., S. Zorzan, and M. Ghoniem. A Methodology for Multilayer Networks Analysis in the Context of Open and Private Data: Biological Application. *Applied Network Science*, Vol. 5, No. 1, 2020, pp. 1–28.
48. Barabási, A. L. Network Science. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, Vol. 371, No. 1987, 2013, p. 20120375.
49. De Domenico, M., A. Sole-Ribalta, E. Omodei, S. Gómez, and A. Arenas. Ranking in Interconnected Multilayer Networks Reveals Versatile Nodes. *Nature Communications*, Vol. 6, No. 1, 2015, p. 6868.
50. City of Norman Open Data. <https://data-normanok.opendata.arcgis.com/>. Accessed July 18, 2022.

51. Oklahoma Department of Transportation. <https://gisokdot.opendata.arcgis.com/>. Accessed July 29, 2022.
52. Pedestrian Safety Tips During Flash Floods. Fourways Review, Janaury 10, 2020. <https://fourwaysreview.co.za/320213/pedestrian-safety-tips-flash-floods/>. Accessed April 26, 2023.
53. Team RC. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, 2013.
54. Esri, R. ArcGIS Desktop: Release 10. Environmental Systems Research Institute, Redlands, CA, 2011.
55. De Domenico, M., M. A. Porter, and A. Arenas. MuxViz: A Tool for Multilayer Analysis and Visualization of Networks. *Journal of Complex Networks*, Vol. 3, No. 2, 2015, pp. 159–176.
56. Pedersen, T. L. Tidygraph: A Tidy API for Graph Manipulation. <https://CRAN.R-project.org/package=tidygraph>. Accessed July 29, 2022.
57. igraph – Network Analysis Software. <https://igraph.org/>. Accessed July 29, 2022.
58. Anselin, L., and X. Li. Tobler’s Law in a MultivariateWorld. *Geographical Analysis*, Vol. 52, No. 4, 2020, pp. 494–510.
59. Moran, P. A. The Interpretation of Statistical Maps. *Journal of the Royal Statistical Society Series B (Methodological)*, Vol. 10, No. 2, 1948, pp. 243–251.
60. Cliff, A. D., and J. K. Ord. *Spatial Processes: Models & Applications*. Pion, UK, 1981.
61. Anselin, L. Local Indicators of Spatial Association—LISA. *Geographical Analysis*, Vol. 27, No. 2, 1995, pp. 93–115.
62. Ukkusuri, S. V., R. Mesa-Arango, B. G. Narayanan, A.M. Sadri, and X. Qian. Evolution of the Commonwealth Trade Network: Hubs, Criticality and Global Value Chains. Commonwealth Secretariat, London, UK, 2016.
63. Kirkley, A., H. Barbosa, M. Barthelemy, and G. Ghoshal. From the Betweenness Centrality in Street Networks to Structural Invariants in Random Planar Graphs. *Nature Communications*, Vol. 9, No. 1, 2018, p. 2501.
64. Mortula, M. M., M. A. Ahmed, A. M. Sadri, T. Ali, I. Ahmad, and A. Idris. Improving Resiliency of Water Supply System in Arid Regions: Integrating Centrality and Hydraulic Vulnerability. *Journal of Management in Engineering*, Vol. 36, No. 5, 2020, p. 05020011.
65. topoBuilder. <https://topobuilder.nationalmap.gov/>. Accessed December 13, 2022.
66. Storm Water Management Model (SWMM). U.S. Environmental Protection Agency, 2014. <https://www.epa.gov/water-research/storm-water-management-model-swmm>. Accessed April 27, 2023.
67. Preliminary Flood Maps for Cleveland County, OklahomaReady for Public View. FEMA.gov. <https://www.fema.gov/press-release/20220208/preliminary-flood-maps-clevelandcounty-oklahoma-ready-public-view>. Accessed December 13, 2022.
68. Porta, S., P. Crucitti, and V. Latora. The Network Analysis of Urban Streets: A Dual Approach. *Physica A: Statistical Mechanics and its Applications*, Vol. 369, No. 2, 2006, pp. 853–866.

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