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# Multi-Network Vulnerability Causal Model for Infrastructure Co-Resilience

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**ABSTRACT** Resilience is mostly considered as a single-dimension attribute of a system. Most of the recent works on resilience treat it as a single-dimension attribute of a system or study the different dimensions of the resilience separately without considering its multi-domain nature. In this paper, we propose an advanced causal inference approach combined with machine learning to characterize the spatio-temporal and multi-domain vulnerability of an urban infrastructure system against extreme weather events. With the proposed causality approach, we perform vulnerability assessment for electricity outages and roadway closures through considering the meteorological, topographic, and demographic attributes of urban areas in the aftermath of the extreme weather events. This proposed holistic approach to multi-network vulnerability assessment paves the ground for characterizing the resilience in a multi-network scheme, which is coined as the concept of "co-resilience." The proposed causal framework for multi-network vulnerability assessment is validated using the actual data for the impacts of the Hurricane Hermine 2016 and the January Storm 2017 on the Tallahassee, FL, USA. The results achieved from the proposed causality approach indicate a high causal relationship among electricity outages, roadway closures, topographic aspects, and meteorological variables in an urban area. Findings show that the proposed multi-network approach for vulnerability assessment improves the performance of the estimation and prediction of the disaster outcomes and the evaluation of the overall system resilience.

**INDEX TERMS** Causality, resilience vs. co-resilience, multi-network vulnerability, extreme events, power outages, roadway closures.

## I. INTRODUCTION

The urban infrastructure and communities relying on these systems are highly vulnerable to extreme weather events such as hurricanes. The need for a holistic assessment investigating the infrastructure resilience has started to draw attention recently due to the increasing frequency of catastrophic hurricanes such as Katrina, Harvey, Hermine, Irma, Maria, and Michael. Just in 2017, the North Atlantic region had experienced 7 hurricanes and 14 tropical storms. These numbers are substantially higher than the 1981-2010 average of 12.1 named storms, 6.4 hurricanes, and 2.7 major hurricanes [1] due to climate change. One such destructive hurricane was Hurricane Michael (2018) with a death toll of 32 people, across the states of Florida, Georgia, North Carolina, and Virginia [2]. Hurricane Michael destroyed almost all communication and left 60 percent of the population homeless in addition to a substantial amount of power outages, roadway closures, and debris. As such, the public frustration and the global impact of such natural disasters call for new paradigms in characterizing, modeling, and enhancing the infrastructure resilience.

There are several studies focusing on the damage of extreme weather events and recovery plans for such events [3]–[7]. Some of the recent studies have investigated the impact of extreme weather conditions on vulnerable populations and searched for more efficient ways for emergency evacuation [6], [8]. Others have specifically performed disasters risk assessment [9], [10]. Among the works on emergency management field, resilience is

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a relatively recent concept compared to the risk assessment and recovery planning. The resilience of infrastructure is defined as the capability of a system to successfully operate during and after disturbances with quick adaptation to perturbations [11], [12]. To be more specific, definition of the resilience is the ability of a system to withstand disruptions with an acceptable degree of performance degradation and recovery with an acceptable amount of cost and time [13]. In the current literature, resilience is generally treated as a single dimensional concept in a given system such as power network. For instance, a recent study quantified the resilience of the power system by coupling various probabilistic fragility models, without considering the impacts of other systems such as transportation/traffic flow on power systems [14].

Electric grids and roadway networks are highly vulnerable infrastructure components during natural disasters. There are a variety of approaches that assess the reliability, resilience, vulnerability and failure process of power and transportation networks individually [15]–[19]. More specifically, the studies on electric grid resilience are mainly focused on the damage to electric grid components, grid partitioning, management of network outages, and prevention of blackouts [20]–[22]. Similarly, there are studies focusing specifically on transportation network roadway closures in the context of emergency resilience as well [23], [24]. However, resilience of a system, by nature, is not an isolated and abstract concept. On the contrary, resilience is a multidimensional manifestation of different states (subsystems) of a system. Therefore, resilience cannot be characterized by a single unit metric. It is a holistic vector of system state variables which are evolving in time, operation, and function.

In the case of infrastructure networks, resilience expands to a multi-domain and multi-network concept with the characteristics of a 'system of systems'. Therefore, the assessment of the risks imposed by disasters on different layers of infrastructure networks serves as the first step to conceptualize the resilience within multi-network systems such as urban infrastructure. As such, a holistic characterization of resilience by considering the interdependence and inter-connectivity among different subsystems of urban infrastructure can lead to better emergency response and preparedness. The multi-network risk assessment metric that includes causal interdependencies paves the ground for faster recovery with lower costs to communities. Within the urban infrastructure, the reliable flow of energy and mobility through electricity and transportation networks ensure the sustainability, security, economic growth, and well-being of communities against disruptions. This paper fills the gap in the existing literature on the infrastructure resilience, which either consider the resilience as a single network problem or study the resilience for different networks separately.

As such, this paper presents a novel multi-network framework for risk assessment in infrastructure systems to achieve the multi-network resilience through proposing a concept named as *co-resilience*. To establish a better understanding of the co-resilience, this paper investigates the inter-operability between electricity and transportation networks in emergency conditions considering the topography and meteorological conditions of the studied area. It is common knowledge that extreme weather events such as hurricanes highly influence human mobility patterns. For example, a fallen tree might lead to both roadway closures and power outages. These closed roadways would also lead to difficulty in accessing the disrupted power lines by the utility crews, thereby increasing the duration of outage recovery. There are some studies that focus on the relationship between roadway closures and weather conditions [20]. There have also been studies based on the prediction of electrical outages on a spatial basis with the use of weather information [25]. However, to the knowledge of the authors, not much has been explored utilizing the inter-connectivity of electricity and roadway networks along with weather condition and topographic parameters during extreme weather conditions. The closest studies to this paper include [26], which suggests a multi-network approach to combine weather data and demographic data with electricity outages. However, [26] does not include the interdependency between different networks such as roadway closures and electric grid outages during extreme weather events, and it does not provide an algorithmic approach to utilize the shared information between different networks.

In this paper, we propose a novel graphical causal model as a multi-domain metric to characterize the inter-operability and interdependency between different layers of infrastructure systems such as electricity and transportation networks combined with topography and weather data, under the influence of extreme weather events such as hurricanes. To the authors' knowledge, causality has not been used as a tool to study and characterize the impact of hurricanes on infrastructure systems in this context. Causality is the mathematical language to express cause and effect relationships between different variables of different nature. There have been few studies that have focused on causality-based characterization of transportation including authors' previous works [27]–[31]. Introducing the concept of causality helps selecting the most informative variables. The causal relationship implies sharing of information between the respective networks. Therefore, in this study, a causal methodology helps us in identifying key variables that impacts electricity outages and roadway closure under extreme weather events. In this study, a novel Deep Neural Network-based causality approach has been proposed to investigate the relationship between power outages, roadway closures, topography, land use, population, and weather-related factors such as wind speed and precipitation. The proposed Deep Neural Network Causality (DNNC) method has been analyzed in detail, and compared with the other state-of-the-art causal methods. A predictive modeling study is performed based on the outcomes of the causal model, which results in the prediction of outages as well as roadway closures using actual data from Hurricane Hermine (2016) and 2017 January storm that have impacted the City of Tallahassee, Florida, USA.

The contributions and novelties of this paper are listed as follows:

1) We propose a novel metric, named as the multi-network vulnerability metric, to characterize the interdependency between electricity, weather, transportation, and topographic systems during and in the aftermath of an extreme weather event.
2) To quantify this multi-network vulnerability metric, a graphical causal model has been proposed.
3) A new causality analysis approach called the Deep Neural Network causality (DNNC) has been developed for better and more accurate description of interdependencies between the infrastructure networks.
4) The proposed multi-network vulnerability assessment metric paves the way to the conceptualization of multi-network multi-domain "co-resilience" in infrastructure networks.

In the following sections of the paper, a comprehensive explanation of the proposed causality theory and other established methods is provided. This is followed by Section III, which provides a detailed description of the proposed causality method, named as the Deep Neural Network Causality (DNNC). This is followed by detailed information on the case studies, namely the two major storms that have impacted the City of Tallahassee, which are Hurricane Hermine (2016) and January Storm (2017). Findings, conclusions and detailed discussions are presented in Sections V and VI, respectively.

## II. MULTI-NETWORK VULNERABILITY & CO-RESILIENCE CONCEPT

As described in the Introduction section, we introduce the concept of multi-network resilience in this paper, which is defined as the integrated resilience of electricity and transportation networks. Urban infrastructures by nature are tangled, interdependent, interconnected, and multi-layered systems of systems. In the face of extreme weather events such as hurricanes, cities experience disruptions and many other adversary effects in different layers. The between systems inter-connectivity and interdependency make the vulnerability assessment and emergency response a very complex task. Therefore, this paper takes the first step towards studying, defining, and designing resilience in urban environments in a multi-network fashion that is named as "Co-Resilience." From an information theory point of view, this co-resilience concept integrates co-dependent networks to take advantage of extra sources of information for outlining the behaviors of interdependent urban networks under extreme weather events. Figure 1 illustrates various infrastructure and topographic layers of infrastructure in the City of Tallahassee, Florida, affected by severe hurricanes in the recent years.

Recently, different mathematical methods have been introduced for modeling interdependencies among different components of infrastructure networks such as statistical approaches [9] and probabilistic approaches [10].

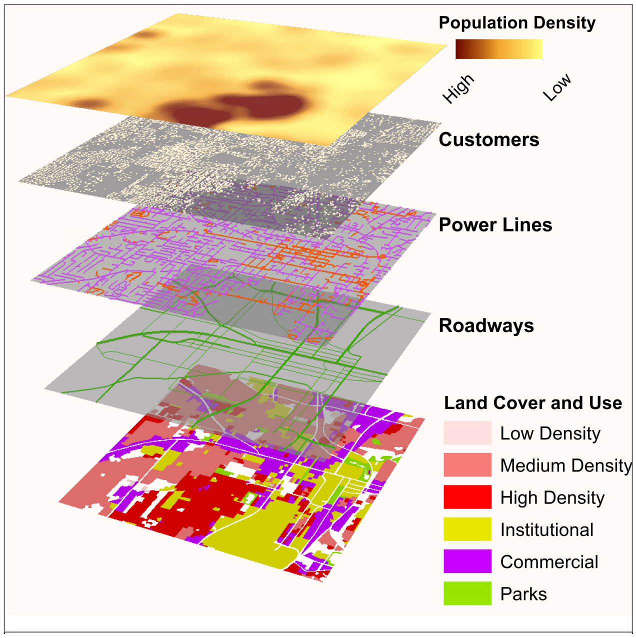



**FIGURE 1.** Multi-layer infrastructure map for the City of Tallahassee, Florida. Layers from top to bottom are population density, all customers, power lines, roadways and land cover respectively.

Graph-based models are among the most capable abstract models of complex networks [32], [33]. In a graph representation, network nodes are connected with edges based on a relationship among those nodes. The causality inference is used graphical models to show the cause and effect relationship between different components of a network's components. Accordingly, in this paper, we utilize a causal graph as the mathematical framework for characterizing the multi-network vulnerability of urban infrastructure under the extreme weather events conditions such as hurricanes.

## III. METHODOLOGY

A synopsis of the methodology followed in this paper is illustrated in Figure 2.

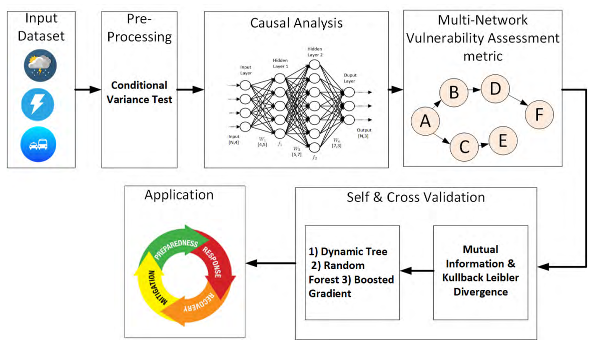



**FIGURE 2.** Overview of the co-resilience characterization methodology.

The input data consist of various temporal and spatial data related to electricity outages, roadway closures, and weather conditions induced by extreme weather conditions along with the topographic data of the affected area. These input data are initially filtered through a first order conditional variance test for causal inference. In order to find the most informative data sources related to the electricity outage, the causal relationship between the input variables is then investigated by a novel causality analysis methodology based on the Deep Learning method. The resultant causal model, which is termed as the *multi-network vulnerability assessment metric*, is then utilized in a predictive modeling study for forecasting power outages and roadway closures that occur under such extreme weather events.

Following sub-sections explain each step of the proposed methodology for multi-network vulnerability assessment towards conceptualizing the co-resilience concept.

### A. MULTI-NETWORK VULNERABILITY ASSESSMENT WITH A CAUSAL GRAPHICAL METRIC

Causality analysis is a theory that describes the relationships between different variables. In other words, causality is a mechanism of quantifying the flow of information from one variable to another. Directed acyclic graphs are formed as a resultant of causal models, which indicate a direct causal relationship regarding the information flow between the variables. A directed acyclic graph is composed of variables (nodes) and arrows between nodes (directed edges) such that the graph is acyclic (i.e., such that it is not possible to start at any node, follow the directed edges in the arrowhead direction and end up back at the same node).

In a general form, a causal model is a classical Bayesian network, which is created by a DAG (directed acyclic graph), where each vertex (node) is labeled by a random variable $x_i$. Let $x = (x_1, x_2, \ldots x_N)$. Arrows represent the causal direction and they are also termed as directed edges. Each node $x_i$ is assigned a transition probability matrix $P(x_i|pa(x_i))$ that depends on the value $x_i$ and the values of $pa(x_i)$. Here, $pa(x_i)$ is the direct causal node of $x_i$ and hence also known as the parent node. The entire Bayesian network is assigned a total probability given as below:

$$P(x) = \amalg_{i=1}^{N} P(x_i|pa(x_i)) \tag{1}$$

For example, if a causal graph denotes $A \rightarrow B$, it is interpreted as $A$ is the direct cause of $B$.

*Definition 1:* Directed Acyclic Graph: DAG is a graph with directed edges. A directed edge is an edge where the endpoints are distinguished as arrow head and tail [33]. In particular, a directed edge is specified as an ordered pair of vertices $(u, v)$ and is denoted by $u \rightarrow v$.

Again, by definition, a directed graph $G = (V, E)$ consists of a nonempty set of nodes $V$ and a set of directed edges $E$. Each edge e of E is specified by an ordered pair of vertices $u, v \epsilon V$.

In the case of causal directed acyclic graphs, the direct dependence is observed by the $d - separation$ [34]. For example, this paper considers a causal chain of variables $A_1 \rightarrow A_2 \rightarrow A_3 \rightarrow A_4$ and also by denoting correlation to measure dependence denoted by $\rho$:

$$\rho(A_i, A_j) \neq 0; i, \quad j = 1, 2, 3, 4 \tag{2}$$

In this paper, causality analysis is applied as a data fusion tool in outlining the most informative variables for the prediction of roadway closures and power outages as interdependent subsystems of urban infrastructure. In the following subsections, the recent state-of-the-art causality analysis models are studied briefly, and then the proposed causal model is presented.

### B. STATE-OF-THE-ART CAUSAL MODELS

Causality is one of the most well known approaches that is used to characterize the dependency and relation between different variables. The most commonly used causality analysis methodologies (Peter Clark's causal model [35], Granger Causality [36], and Structural Equation Modeling [37]) are described in Table 1.

**TABLE 1.** State-of-the-art causal methodologies.

| Causality Method | Description | Reference |
|---|---|---|
| Peter Clark | Causal graph formed based on values from Conditional Independence test $P(X\|Y,Z) = P(X\|Z)$ | [35] |
| Granger Causality | Causal relationship achieved by Simple Linear regression on bi-variate series $y(t) = \sum_{i=1}^{\infty} \alpha_i y(t-i)$ $+ \sum_{i=1}^{\infty} \beta_i y(t-j) + c + v(t)$ | [36] |
| SEM | Categorizing variables and then applying linear relationship test $y_t = f_t(PA_t, v_t)$ Where $t = 1, 2, ..n$ $PA_i$ is parent & $u_i$ is error | [37] |

The methodologies discussed in Table 1 have some drawbacks based on experiments and performed studies in the literature. Granger Causality has a limitation while considering seasonalities and variations in time-series in the study. Also, when seasonality is introduced, Granger causality is more cryptic in comparison with other causality methodologies. Similarly, while specifying the latent class of structural equation model, spurious results can be achieved if a category is unspecified. In addition, SEM is originally designed for the analysis of the relationships between latent variables. However, diagnostic experts wish to know the values of latent variables (i.e., the factor scores) for individual subjects, which can be estimated in SEM. However, these estimations bear severe problems as factor scores may be derived in different ways yielding different results. In order to reduce such uncertainties and weakness in causal relationship modeling, a deep neural network based causal approach has been proposed in this paper, which yields a more accurate direct causal relationship due to different layers of training. There have been very few works focusing on the use of neural networks in understanding such causal relationships. Neural Networks have the ability to learn and model non-linear and complex relationships, which enhances the information from real world data sets.

### C. DEEP NEURAL NETWORK CAUSALITY (DNNC) MODEL

Neural Networks are a critical component of Machine learning which, owing to their complex structures, serve as one of the best structures in time series data analysis. Neural networks (NN) consist of a group of algorithms that are modeled based on a human brain structure, which is capable of pattern recognition. The NN recognize patterns that are contained in vectors, into which all real-world data including images, sound, text or time series can be translated. Deep neural networks, on the other hand, are neural networks that consist of more number of hidden layers for the processing of the given input data. There have not been many studies considering neural networks in causal mechanisms [32]. The training methodology used in neural networks along with forward and backward propagation can help in the better prediction of causal relationships. Therefore, in this paper, a causality methodology is proposed which utilizes the concept of deep neural networks in order to better characterize the interdependent variables.

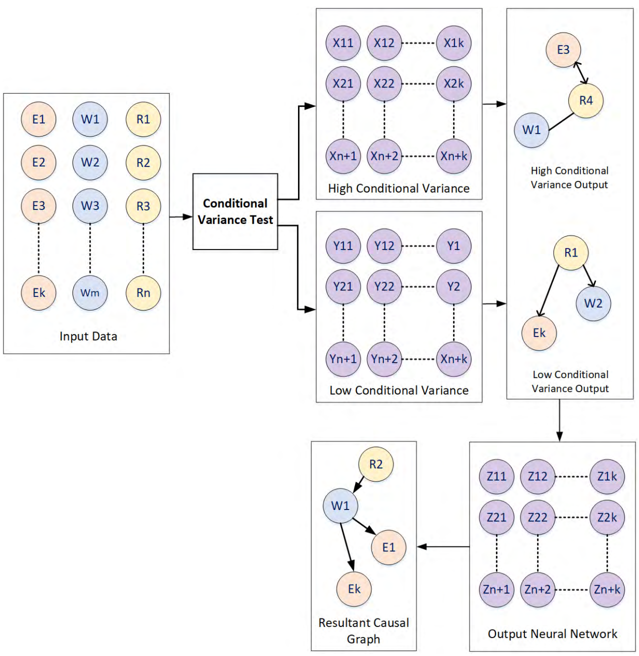



**FIGURE 3.** Overall architecture of the proposed DNNC Model.

Suppose $\{R_1, R_2, ..R_n\}$,$\{W_1, W_2, ..W_m\}$,$\{E_1, E_2, ..E_k\}$ are different time series input data sets representing roadway closures, weather and power outages, respectively. The inputs are first filtered based on the conditional variance. The variables with high conditional variances, denoted by $X = X_1, X_2, X_3, \ldots, X_n$, are fed into the first set of hidden layers. Similarly, $Y = Y_1, Y_2, Y_3, \ldots, Y_n$ are inputs to the second set of hidden layers consisting of low conditional variance. Based on the conditional variance training, the outputs are filtered and associated as shown in Figure 3. The outputs from these two respective hidden layer form causal graphs between filtered variables based on the conditional variance. These selected variables are again fed into the final deep neural network output layer. The architecture of this deep neural network causality is illustrated in Figure 3.

The Conditional variance shows the variance of a random variable given the values of one or more other variables. Consider two distinct variables X and Y. The conditional mean of Y given X $= x$ is defined as below:

$$\mu_{Y|X} = E[Y|x] = \sum_y yh(y|x) \tag{3}$$

The conditional variance of Y given X $= x$ is given as:

$$\sigma^2_{Y|X} = E[Y - \mu_{Y|x}]^2|x = \sum_y [Y - \mu_{Y|x}]^2 h(y|x) \tag{4}$$

After categorizing the inputs based on the conditional variance, activation functions are applied to initiate the functioning of the hidden layers of the deep neural network causality. The two most common activation functions are the logistic sigmoid and hyperbolic functions.

$$g_{logistic}(z) = \frac{1}{1+e^{-z}} \tag{5}$$

$$g_{tanh}(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \tag{6}$$

Since there are no inter-layer connections, the state of the visible and hidden layer are conditionally independent to each other. Then, the probability of a specific node to turn on is given as:

$$p(h_j = 1|v) = \sigma(b_{h,j} + v^T W_j) \tag{7}$$

where $\sigma(x) = \frac{1}{1+e^{-x}}$ and $W_j$ represent the j-th column vector of the matrix W. This performs the k-step Gibbs sampling to generate a reconstructed form of the given training data. As observed in Figure 3, a resultant causal graph is the output of the final neural network structure. This causal graph yields the interrelationships between different input variables.

*Definition 2:* Multi-Network Vulnerability Assessment Metric: Multi-network vulnerability assessment metric is the outcome of the proposed DNNC model. The inputs to the DNNC causal model consist of roadway closures ($R$), power outages ($E$) and weather variables ($W$). In other words, the vulnerability assessment metric is represented as a graph with vertices $V \subset R, E, W$.

## IV. VALIDATION APPROACH FOR THE PROPOSED MULTI-NETWORK VULNERABILITY METRIC

The ideology and contributions of this paper are not just limited to characterizing the connection and dependency between different infrastructure networks. This paper also aims to quantify the underlying cause and effect relationships between electricity networks, roadway systems, topography of the region and meteorological variables to understand and estimate the impact of hurricanes on the urban infrastructure.

The first step in validation is testing causal models using information theory indices, which is referred to as "self validation" in subsection IV. 1. The second stage of validation is through performing electricity outage estimation using the resultant causal model, where it is referred to as the "cross validation" in section IV.B.

Based on the resultant causal graphs, the variables that have a direct cause on outages are considered as predictor variables. Using actual data from the Hurricane Hermine that impacted the City of Tallahassee, Florida in 2016, an electricity outage and roadway closure estimation and prediction test was then performed as a cross validation in order to show the impact of resultant causal outcomes.

#### 1) MULTI-NETWORK VULNERABILITY METRIC SELF VALIDATION

Causality is a mechanism that implies the flow of information from one series to another. The outcome of causality analysis is a DAG graph as mentioned earlier. First step towards validation of a causal graph is quantifying the amount of information flow or similarity index between two nodes that are conned with a edge. For this purpose, two information theory based metrics have been used in this paper. These metrics quantify the information shared between different nodes and the direction of the flow of information as depicted by the edges connecting the respective nodes.

1) Mutual Information: Mutual information (MI) is in several ways a perfect statistic for measuring the degree of relatedness between data sets. The MI between two data sets X and Y can be estimated from the statistics of the (x,y) pairs between the two data sets. The Mutual Information I(X,Y) between the systems X and Y is defined as shown in the equation below:

$$I(X, Y) = H(X) + H(Y) - H(X, Y) \geq 0 \tag{8}$$

2) Kullback-Leibler Divergence: Measuring the disparity between two probability distributions over the same variable $x$ is called the Kullback-Leibler divergence (KLD). The KLD is a measure of the difference between the two probability distributions $p(x)$ and $q(x)$ with a discrete random variable $x$. The KLD between the two distributions is achieved as shown below:

$$KLD(p(x)||q(x)) = \sum_{x \epsilon X} p(x) ln \frac{p(x)}{q(x)} \tag{9}$$

#### 2) MULTI-NETWORK VULNERABILITY METRIC CROSS VALIDATION

The theory of causality suggests that any direct causal relationship between two variables signifies the flow of information between them. In this paper, the objective is to estimate the impact of a hurricane on electricity outages and roadway closures occurring as a result of extreme weather events. The crucial factors affecting electricity outages are wind speed, roadway closure, soil moisture, land cover and drainage system. The resultant causal model specifies the most informative direct causal variables which can be utilized as predictors in predicting electricity outages occurring as a result of extreme weather events. For example, wind speed, rain rate, and vegetation are generally considered as the main reasons for electricity outages, but utilizing causality also helps us in examining the underlying causes such as roadway closures, soil moisture and other topographic indices which are latent variables. In other words, direct causal links and the shared information between the infrastructure networks (roadway network, the electric grid, and the city topography) are utilized to predict the co-dependent vulnerability of each network during extreme weather conditions. The apparent and latent direct causal variables are then used as predictors in the estimation of electricity outages as shown in Figure 2, which are the inputs for the predictive modeling study. Three state-of-the-art regression based data forecasting methods have been used in this paper as follows:

1) Decision Tree Regression (DTR): It is a collection of logical "if-then" statements which are termed as branches. This relates the explanatory variables (precipitation, wind speed, temperature, etc.) to a response variable (affected number of customers) by recurrently separating the explanatory variables onto bins termed as leaves which minimizes the sum of square error [38].
2) Random Forest Regression (RFR): A decision tree passes through the data once, a random forest regression bootstraps 50% of the data and develops several trees. Instead of utilizing all explanatory variables, a random group of the variables are chosen for splitting [39].
3) Boosted Gradient Regression (BGR): A predictive model is developed by a group small trees that are built on remainders of the past trees. Addition of more layers to the tree, the contribution from each small tree is regulated by a learning rate. The sum of predictions become more accurate along with the increasing depth of the tree [40].

## V. STUDY DATA

As a validation-based application for the proposed causal model, a predictive analysis is performed on real-world data sets. The co-resilience graphical metric is utilized to predict real-world spatial power outages that occurred as a result of the Hurricane Hermine (2016) and January 2017 storm in the City of Tallahassee. Tallahassee is the most populated city in the Leon County, which houses 286,272 people. The urbanized area of Tallahassee has a population of 190,894 according to the U.S. Census estimates. Tallahassee is a municipality that provides gas, sewer, electricity and other public community services to the region. Along with the power outages data, roadway closure data was considered to construct the Co-resilience graphical metric. In addition to roadway closures and electric power outages, weather parameters such as Wind speed, Precipitation, Temperature,

**TABLE 2.** **Input data description.**

| Variable | Description |
|---|---|
| Electric Feeders Affected (EF) | Number of feeders affected by power outages |
| Road Closure (RC) | Number of roadways closed due to Hurricane impact |
| Wind Speed (WS) | 1 minute wind gusts ($ms^{-1}$) |
| Rain Rate (RR) | Amount of rainfall (mm/hr) |
| Temperature (T) | Temperature ($^{\circ}F$) during hurricane |
| Land Cover (LC) | Barren, Urban, Herbaceous, shrub, forest |
| Soil Moisture (SM) | Soil Moisture in % |
| Soil Temperature (ST) | Soil Temperature ($^{\circ}F$) |
| Drainage system (DS) | Classification into well and poorly drained systems |

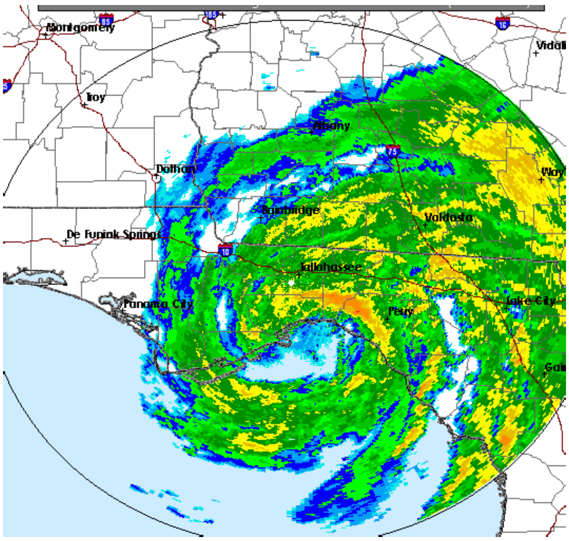



**FIGURE 4.** **Hurricane Hermine path, September 1, 2016 [1].**

**TABLE 3.** **Hurricane Hermine statistics and vital facts.**

| Variable | Description |
|---|---|
| Landfall | September 1, 2016 |
| Highest sustained winds | 80 $mph$ |
| Central Pressure | 981 $mb$ |
| Resulting Power Outages | 325,000 people |
| Damage Assessment | $550 million |

Humidity and pressure as well as several topographical factors were also taken into account.

### A. HERMINE HURRICANE (2016)

Hurricane Hermine hit the Florida Panhandle Gulf Coast on September 1st, 2016, and disrupted many key services in Tallahassee such as power and transportation from 10:00 PM of September 1st, 2016 to 4:00 AM of the next day September 2nd, affecting thousands of customers. 100,000 City of Tallahassee and Talquin Electric Company customers were without power the morning after the storm and many roadways were disrupted. It was the first hurricane to make landfall in Florida Panhandle region in 11 years. The path of Hurricane Hermine is illustrated in Figure 4.

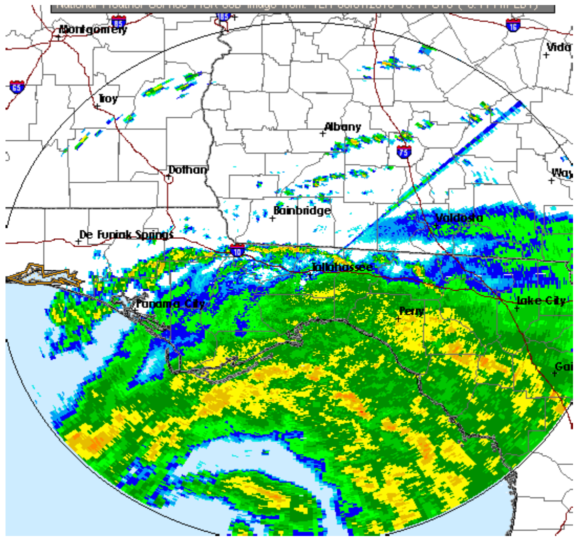



**FIGURE 5.** **January storm path, January 22, 2017 [1].**

**TABLE 4.** **January 2017 Storm statistics and vital facts.**

| Variable | Description |
|---|---|
| Severe Storm | January 21, 2017 |
| Highest sustained winds | 50 $mph$ |
| Resulting Power Outages | 50,000 people |

### B. JANUARY 2017 STORM

A severe weather event struck the southeast on January 21, 2017 with three rounds of severe weather moving through the area, the first round starting during the mid-morning hours on Saturday, January 21, 2017 as a squall line pushed into southeast Alabama and the Florida panhandle [1]. Figure 5 illustrates the path and trajectory of the January 2017 storm. As a result of this tropical storm in January, approximately 50,000 customers were without power and many roadways were closed in Tallahassee.

### C. USING SYNTHETIC DATA SET FOR CAUSAL MODEL VALIDATION

The proposed causal model is also applied on a synthetic data set, which strengthens the proposed approach due to prior knowledge of the expected ground truth of the causal structure. We design two types of data sets, namely the data sets with the normal distribution and the data sets with local-distribution-shift samples. The algorithm defined below is utilized to generate the synthetic data set:

## VI. RESULTS AND DISCUSSIONS

This work is aimed at identifying interdependencies between different variables in order to select the most informative variables as predictors for an extreme event-based impact prediction. Findings achieved from the proposed multi-network vulnerability assessment metric are further classified into three different subsections based on their applications and case studies.

**Algorithm 1** Algorithm to Achieve Synthetic Data Set for Causal Model Validation

**Input** : Set of 5 time series variables $X_1, \ldots X_5$

$X_1(t) = X_1(t) + 1.34 * X_1(t-1) - 0.9025 * X_1(t-2)$

$X_2(t) = X_2(t) + 0.5 * X_1(t-2)$

$X_3(t) = X_3(t) - 0.4 * X_1(t-3)$

$X_4(t) = X_4(t) - 0.5 * X_1(t-2) + 0.35 * X_4(t-1) + 0.35 * X_5(t-1)$

$X_5(t) \rightarrow X_5(t) - 0.35 X_4(t-1) + 0.35 X_5(t-1)$

**Output**: $X_2 \leftarrow X_1 \rightarrow X_3, X_4 \leftrightarrow X_5$

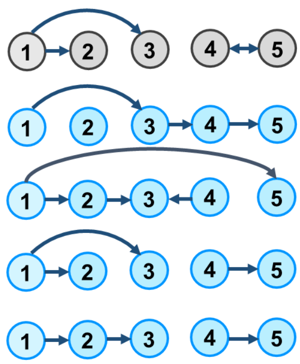


**FIGURE 6.** Causal models for synthetic data set from top to bottom: (a) Ground truth causal model for the Synthetic Data set (b) Granger causality (c) PC causal model (d) DNNC and (e) SEM.

### *A. DNNC CAUSAL MODEL VALIDATION WITH SYNTHETIC DATASET*

The proposed causal model was first applied on the synthetic data set, which serves as a validation for the causal approach since the ground truth for the synthetic data is known. As seen in Figure 6, (a) is the ground truth causal model for the synthetic data set. From figure 6 (b)-(e), it is observed that DNNC results are in a similar causal structure as the ground truth causal model. To validate this further, two information theory-based metrics are chosen, namely Mutual Information (MI) and Kullback Leibler Divergence (KLD). While MI quantifies the amount of flow of information between different variables, KLD signifies the divergent behaviors of the variables. A higher value of Mutual Information signifies a better causal model consisting of more information sharing between different variables. However, a lower value of Kullback-Leibler Divergence signifies more information sharing between two nodes of a causal graph. Table 5 enumerates the values for different causal models applied on the synthetic data set.

**TABLE 5.** MI and KLD values for different causal models.

| Method | Granger | PC | SEM | DNNC |
|---|---|---|---|---|
| MI | 0.62 | 0.65 | 0.61 | 0.93 |
| KLD | 0.48 | 0.32 | 0.55 | 0.29 |

As observed in Table 5, a higher value of MI was achieved for the DNNC-based causal approach. This indicates more information sharing between the direct causal variables. Also, a lower value of KLD implies more information sharing or lesser divergent behavior. DNNC achieves a lower

**TABLE 6.** Estimation error (MAPE) for Synthetic Data set-based comparison of various estimation methodologies.

| Causal Approach | DTR | RFR | BGR |
|---|---|---|---|
| DNNC | 0.16 | 0.13 | 0.11 |
| SEM | 0.33 | 0.37 | 0.41 |
| PC | 0.26 | 0.22 | 0.19 |
| MGC | 0.48 | 0.42 | 0.33 |

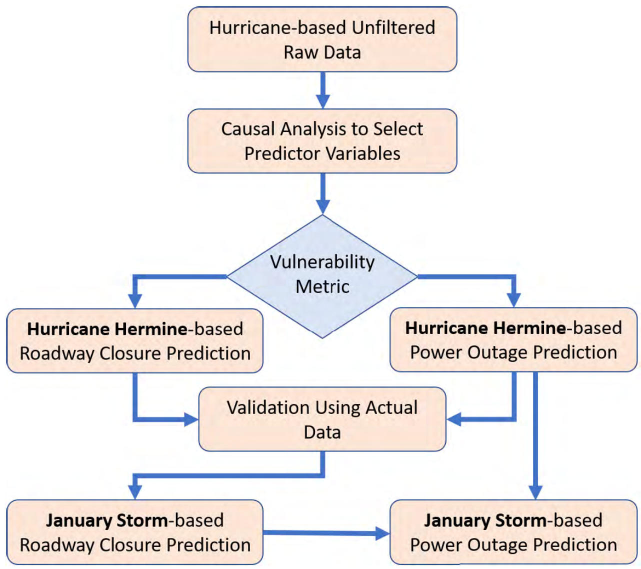



**FIGURE 7.** Block diagram for the predictive analysis methodology based on the multi-network vulnerability assessment metric.

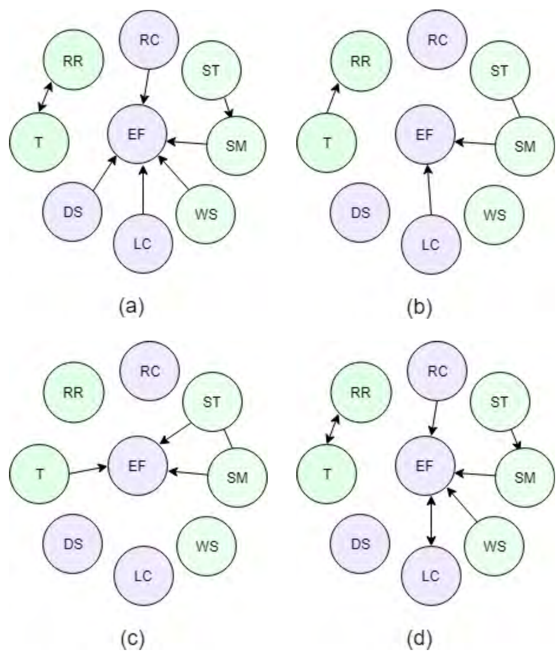
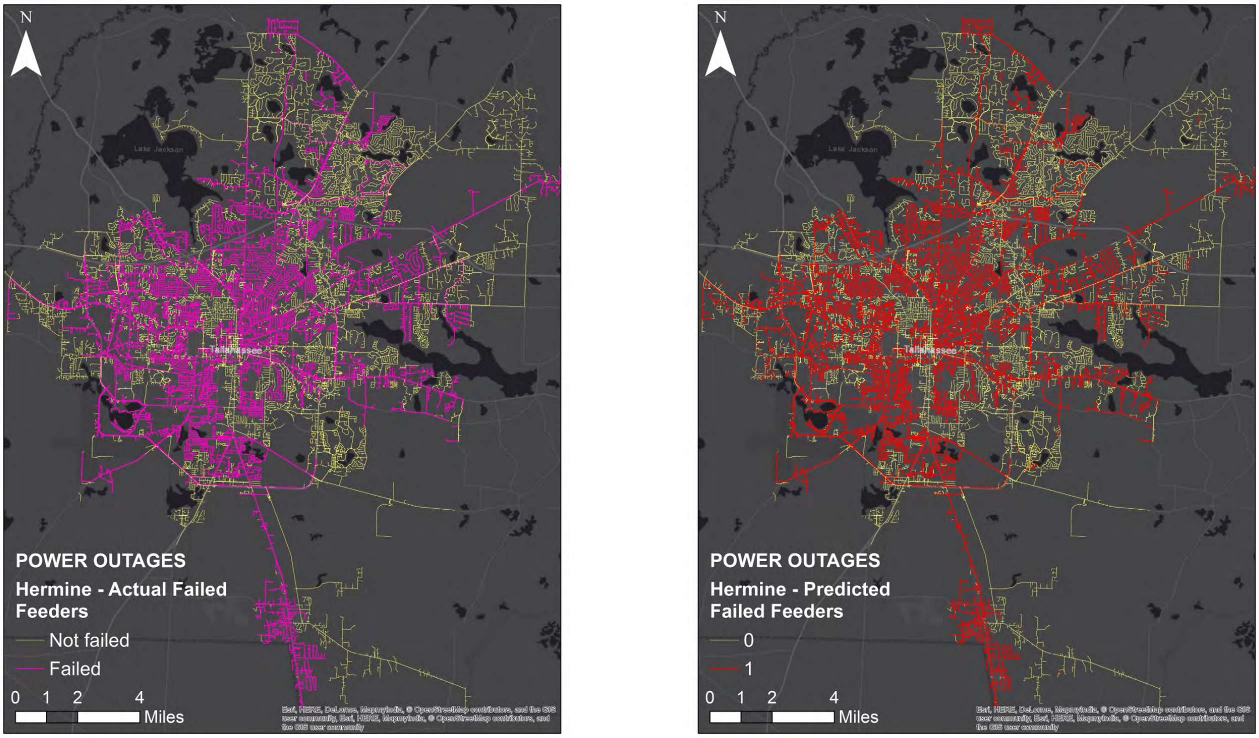



**FIGURE 8.** Causal model outcomes for Hurricane Hermine from (a) DNNC, (b) PC, (c) SEM and (d) Granger methodologies.




(a) (b)

**FIGURE 9. Actual vs predicted power outages during Hurricane Hermine. (a) Actual power outages during Hurricane Hermine. (b) Predicted power outages during Hurricane Hermine.**

value of KLD thereby strengthening the causal relationships detected. The synthetic data set was also utilized in a predictive modeling study. Note that the different predictive methodologies utilized were explained in the Methodology section. The prediction error percentages for the synthetic data are listed in Table 6.

From Table 6, it is observed that, Deep Neural Network Causal method provides the most accurate results when applied to the synthetic data set and combined with the Boosted Gradient Regression-based forecasting technique. The accuracy of 89% has been achieved in the case of synthetic data set.

### B. ESTIMATION OF ELECTRIC OUTAGES & ROADWAY CLOSURES: HURRICANE HERMINE CASE

The main objective of this paper is to perform a multi-network vulnerability assessment. For better validation, we use two real world data sets as discussed in Section III. The validation strategy is illustrated in Figure 7.

As seen in Figure 7, the first step is to create a causal model which represents the multi-network vulnerability assessment metric in order to select the most relevant and informative variables among inputs that yield to a better outage prediction. Based on the causal relationships achieved, a validation is performed using the actual power outage and roadway closure data during Hurricane Hermine. However, due to the lack of original roadway closure data for the January storm, we use the Hurricane Hermine roadway closure data as training data along with weather and power outage data from the January storm in order to predict roadway closures occurring as a result of the January storm. The predicted roadway closure data for the January storm is combined with other weather variables pertaining to the storm in order to predict the power outages occurred due to the January storm itself.

Using the proposed DNNC causal model and other aforementioned causality methods, the causal graph for multi-network vulnerability assessment is created as illustrated in Figures 8a - 8d. These figures also provide a way to compare the causal graphs obtained for the proposed multi-network framework. Note that Figures 8(b), (c) and (d) illustrate the outcomes of other state of the art causality methodologies whereas 8(a) shows the results associated with the proposed methodology. DNNC approach identified both roadway closures, outage duration, number of affected customers and population as variables that are interrelated whereas other models generally did not have roadway closures as one of the important factors for outage prediction. The DNNC causal graph as shown in Figure 8 (a) is thus referred to as the multi network vulnerability model since it directly relates power outages with roadway closures including weather parameters. Granger model 8(d), however failed to show the relation between land cover, power outages and

**TABLE 7. MI and KLD values for the causal models.**

| Method | Granger | PC | SEM | DNNC |
|---|---|---|---|---|
| MI | 0.59 | 0.74 | 0.57 | 0.89 |
| KLD | 0.71 | 0.44 | 0.63 | 0.21 |

roadway closures. Moreover, both roadways and power lines should be related due to the affect of fallen trees as observed clearly during Hurricane Hermine.

From Table 7, it is observed that the highest values of MI are achieved for the DNNC causal model in comparison to the other state of the art causal methodologies. A higher number of MI reveals more information flow between the variables. Meanwhile, a lower number of KLD reveals more similarity between the variables. It is observed from the Table 7 that DNNC achieves lower values of KLD.

Based on the values enumerated in the Table 7, it is observed that DNNC-based causal model has the least amount of divergence. Also, the mutual information number is higher in comparison to the other causal models. This implies that significant amount of information is shared in the direct causal variables as estimated by the DNNC causal model.

The cross validation was then performed as a second step validation of the causal models. As mentioned in **Section 2.3 B**, different regression-based predictive modeling techniques were performed for the estimation of power outages and feeder failures during Hurricane Hermine. Therefore, based on the DNNC model, the inputs used as predictors for the prediction of power outages in case of Hurricane Hermine includes roadway closure, soil moisture, wind speed, land cover and drainage system data. Similarly, for the prediction of roadway closures, power outage data was used along with wind speed, land cover and soil moisture as inputs. Figures 9 and 11 illustrate the spatial distribution of the actual Hermine power outages and roadway closures along with the respective predictions for the Hurricane Hermine impacts. The error in power outage prediction can be observed in Figure 10. As observed from the Figure 10, the error is significantly lower when DNNC-based causal model was utilized to select the predictor variable. Figure 10 shows that the proposed method fails to predict outages (shown in red in Figure 10) at certain locations clustered around the Northwestern region of Tallahassee. This may be attributed to the sparsity of weather-related data available at these locations. This is also observed for the falsely predicted power outages (shown in blue in Figure 10) in some of these areas, similarly due to the sparsity of the available weather data stations. Similarly, Figure 12 illustrates the error in roadway closure predictions for the Hurricane Hermine. False predicted as Closed, highlighted in blue color in Figure 12 implies a roadway falsely predicted as closed (a roadway that was open). On the other hand, False predicted as not closed shown in red in the Figure 12 implies predictions which failed to recognize actual closures.

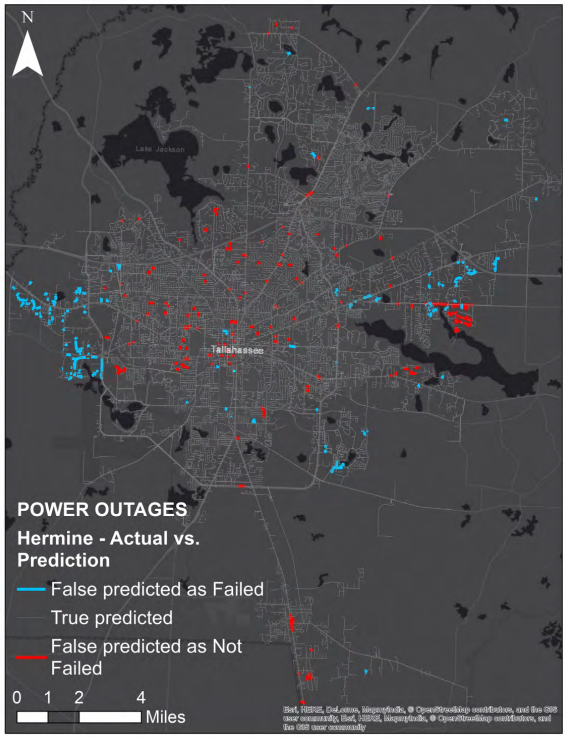



**FIGURE 10.** Prediction error for power outages during Hurricane Hermine.

To evaluate the achieved prediction and compare it with the actual values, different error indices were used. Mean Absolute Percentage Error (MAPE) is a commonly used metric in order to investigate the prediction accuracy of a forecasting method. It usually expresses the accuracy as a percentage. The MAPE values were calculated for all the aforementioned prediction methodologies.

$$MAPE = \frac{100}{n} \sum_{t=1}^{n} |\frac{y - y'}{y}| \tag{10}$$

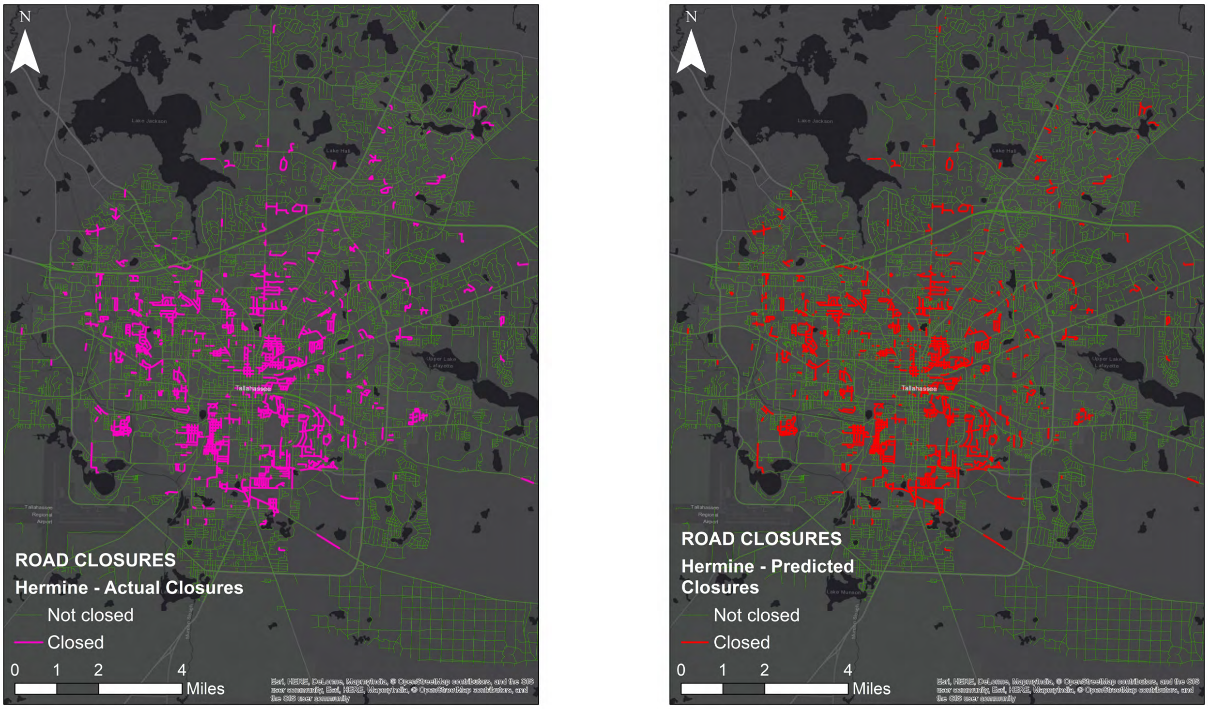
In the above equation, $y$ is the actual observation, $y'$ is the predicted observation and $n$ is the sample size of the data set.

**TABLE 8. MAPE for feeder outage prediction during Hurricane Hermine.**

| METHOD | Granger | SEM | PC | DNNC | No Causal |
|---|---|---|---|---|---|
| DTR | 15.93 | 9.72 | 7.33 | 6.93 | 25.33 |
| RFR | 15.11 | 9.65 | 7.05 | 6.86 | 21.76 |
| BGR | 12.32 | 7.71 | 6.93 | 6.17 | 21.14 |

Table 8 represents the accuracy of the three regression-based methods along with the causal methodologies considered for the power outage estimation for the Hurricane Hermine.

It is evident from the tables 8 that DNNC outperforms other causal models. The least value of MAPE is achieved when DNNC-based causal model is applied in combination with the Boosted Gradient Tree Regression based prediction.




(a) (b)

**FIGURE 11.** Actual vs. predicted road closures during Hurricane Hermine. (a) Actual road closures during Hurricane Hermine. (b) Predicted road closures during Hurricane Hermine.

**TABLE 9.** MAPE for roadway closure prediction during Hurricane Hermine.

| METHOD | Granger | SEM | PC | DNNC | No Causal |
|---|---|---|---|---|---|
| DTR | 16.16 | 15.88 | 13.13 | 11.54 | 31.76 |
| RFR | 16.21 | 14.66 | 14.11 | 11.98 | 30.33 |
| BGR | 15.11 | 10.01 | 10.86 | 9.46 | 30.01 |

**TABLE 10.** MAPE for feeder outage prediction during the January Storm.

| METHOD | Granger | SEM | PC | DNNC | No Causal |
|---|---|---|---|---|---|
| DTR | 26.86 | 25.91 | 22.43 | 21.62 | 37.32 |
| RFR | 26.24 | 24.81 | 23.12 | 20.94 | 34.41 |
| BGR | 26.11 | 20.66 | 18.53 | 19.87 | 29.49 |

Similarly, the roadway closure estimation yields error percentages as enlisted in Table 9. Again, a similar trend is followed, and the highest accuracy is achieved by the DNNC-based causality method in combination with BGR methodology-based estimation.

### C. FORECASTING ELECTRIC OUTAGES & ROADWAY CLOSURES: JANUARY STORM 2017 CASE

In case of the January storm 2017, historical data from the impact of Hurricane Hermine was considered as a training data set along with weather and power outage data from the January storm in order to predict roadway closures occurring as a result of the January storm. The predicted roadway closure data for the January storm is combined with other weather variables pertaining to the storm in order to predict the power outages occurred due to the storm itself. Table 10 represents the error percentages for the case of power outage prediction due to this storm. Table 10 is in agreement with the other prediction errors reported, and DNNC combined with Boosted Gradient regression provides the most accurate power outage predictions.

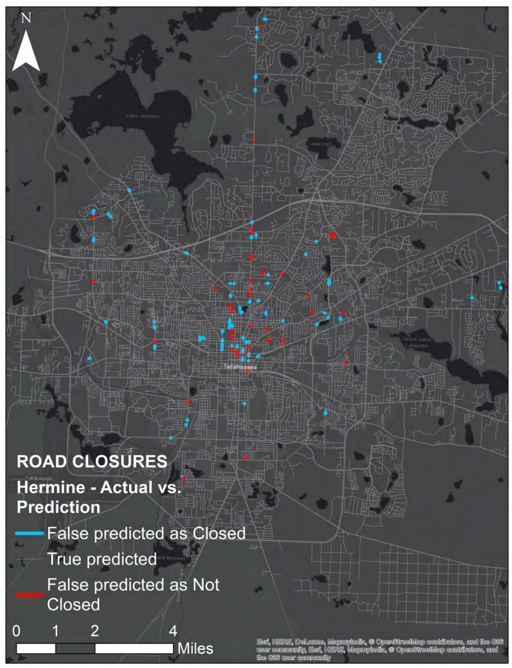
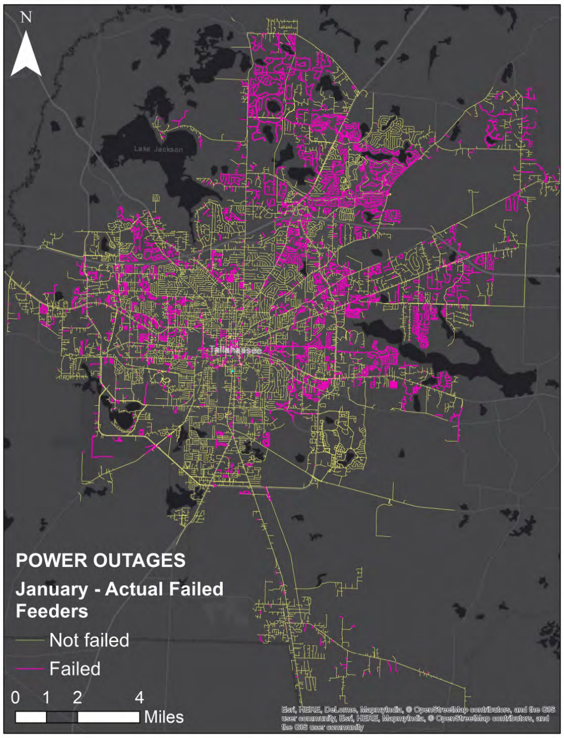
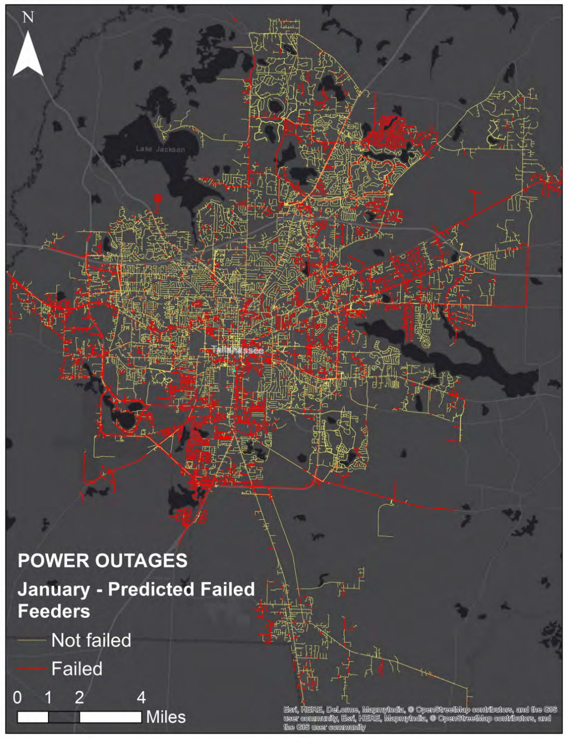



**FIGURE 12.** Prediction error for roadway closures during Hurricane Hermine.




(a)




(b)

**FIGURE 13. Actual vs Predicted power outages during the January Storm. (a) Actual power outages during the January storm. (b) Predicted power outages during the January storm.**

In order to better understand and judge the predictive capability of this model, Figure 13 illustrates the comparison between actual feeders affected and predicted feeders affected due to the January storm.

The spatial density of the feeder outages are illustrated in Figure 13. Based on the outcomes of DNNC causal model and Boosted Gradient Regression, the prediction of feeders affected during January storm is illustrated in Figure 13b. By comparing 13b with 13a, it is observed that DNNC combined with BGR-based prediction method provides a significantly accurate prediction of feeder failures. Due to the lack of roadway closure data in case of the January storm, a lower accuracy of prediction is thus achieved when compared with the findings of Hurricane Hermine. In order to overcome this limitation, a roadway closure prediction was first performed by utilizing the same model obtained for Hurricane Hermine, but using data from January storm in this case. This roadway closure prediction as illustrated in Figure 15 is then utilized for the prediction of power outages for the January storm. Although following this approach yields lower roadway closure predictions for the January storm, note that the January storm was much lower in intensity and thus, had a significantly lower impact in comparison with Hurricane Hermine. It is observed that, due to lack of actual roadway closure data and vegetation data for the January storm, the prediction accuracy is comparatively lower than during the case of Hurricane Hermine. This is illustrated in Figure 14. The prediction accuracy is higher when roadway closure data is accounted for in the outage prediction, which strengthens the concept of the proposed co-resilience metric.

On comparing the prediction error of power outages during Hurricane Hermine as seen in Fig.10 with the prediction error of power outages during January storm shown in Fig.14, we observe a higher value of error in the case of January storm. This limitation in the methodology is the lack of available high resolution spatial data. In other words, the variables considered in this study have different time steps and different sample sizes. This is one limitation of DNNC causal model, where a lower value of accuracy is obtained for time series with different time steps and different sample sizes. Despite the limitations, the higher accuracy obtained is accounted to the advantages of applying a causal-based methodology for the impact predictions under extreme weather events.

### D. TAKE-AWAY FROM THE IMPACT OF CAUSALITY ON PREDICTION ANALYSIS

In order to evaluate the advantages of applying a causality based prediction approach, it is important to examine the effect of each direct causal and non-causal variable one by one for the prediction. To do this, power outage predictions were performed using a single variable as input.

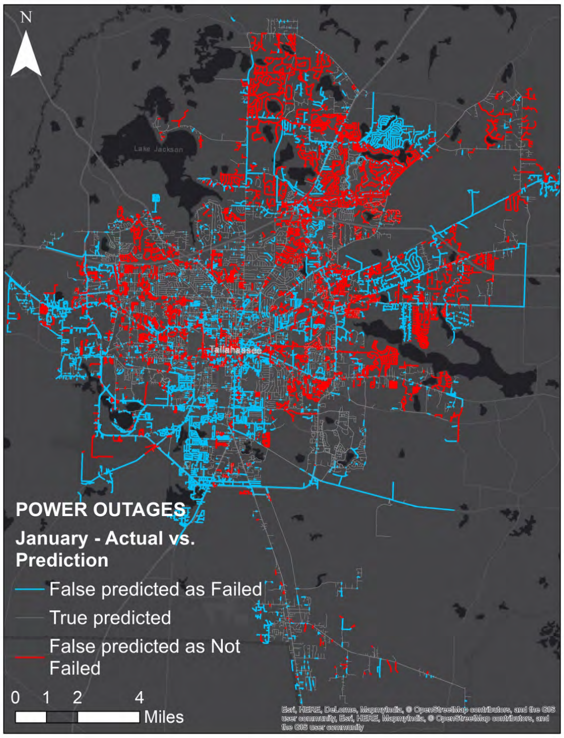



**FIGURE 14.** Prediction error in power outage prediction for January storm.

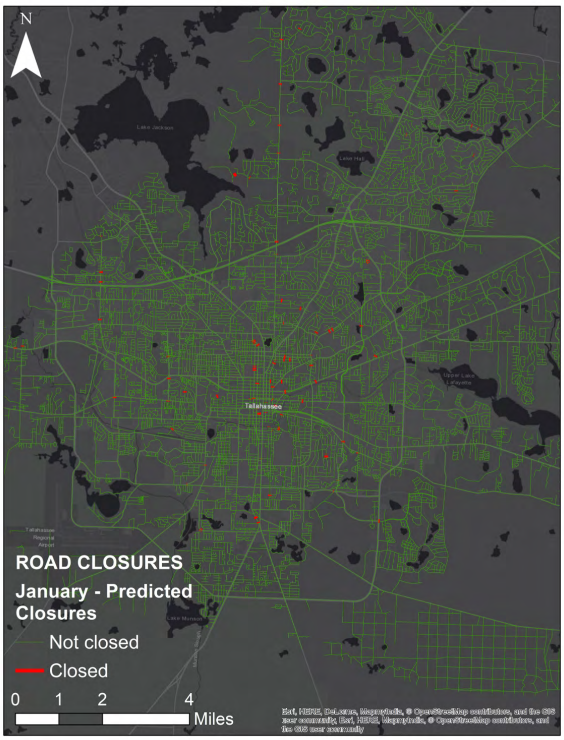



**FIGURE 15.** Roadway closure prediction for the January storm.

Therefore, following variables have been added one by one to the number of failed electric feeders (EF) to estimate the power outage (EF) during hurricane Hermine:

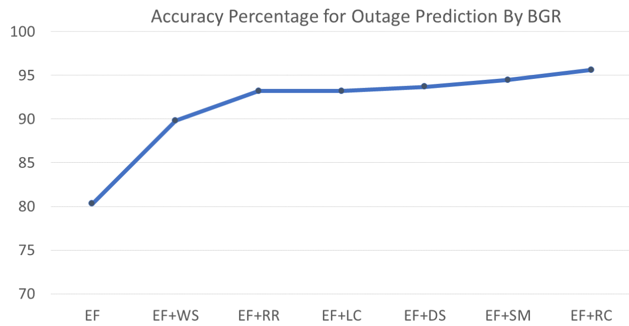



**FIGURE 16.** Accuracy percentage for different combinations of Input variables for Hurricane Hermine based predictions.

the wind speed (WS), the number of failed electric feeders (EF), Rain Rate (RR), Land Cover (LC), Drainage system (DS), Soil Moisture (SM), and Roadway Closure (RC). In Figure 16, it is observed that the power outage prediction error is higher when the input consists of EF variable only. Adding RC information to EF as an input significantly reduces the power outage perdition error compared to other variables.

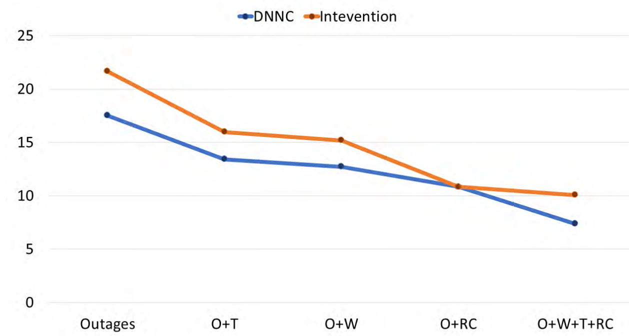



**FIGURE 17.** Intervention analysis on combination of Input variables for Hurricane Hermine based predictions.

The advantages of applying the proposed causality-based approach is also evident from Figure 17. This figure compared the outcomes of outage prediction models with varying input combinations. It is observed that the error is higher when outage prediction was performed with intervention, by utilizing 'outages' data only. The error reduces when outage data is combined with topographic data (O + T). A similar trend is seen when outage data is combined with weather data (O + W). It is to be noted that the error further reduces when prediction is performed by combining outages data with road closure data (O + RC). The accuracy is highest when historical outage data is combined along with other variables such as weather, topography and roadway closure (O + W + T + RC) information. This similar pattern is observed when a DNNC model based prediction is performed by combining only the direct causal variables such as soil moisture and wind speed under weather variables, soil moisture under the topography variables, thereby strengthening the need for causal based input selection process.

## VII. CONCLUSION

In this paper, we conceptualize the theory of Co-Resilience utilizing causality approaches in order to understand the interdependence between different infrastructure networks during extreme weather events. A novel Deep Neural Network based causality (DNNC) methodology was proposed for this purpose, and the resultant multi-network vulnerability assessment metric characterizes the direct dependency between power outages and roadway closures combined with weather and topology-based parameters. This approach can significantly strengthen the resilience of different infrastructure networks fused together. The developed multi-network vulnerability assessment metric was utilized as a predictor model to estimate power outages and roadway closures induced by the 2016 Hurricane Hermine and 2017 January storm that have impacted the City of Tallahassee, Florida. Results indicate high accuracy performance of the model in the prediction of power outages as well as roadway closures. For example, for the Hurricane Hermine, the power outages were estimated with a 93.83% accuracy. Roadway closures, on the other hand, were predicted with an accuracy of 90.54% for the Hurricane Hermine case. Similarly, power outage prediction due to the January storm was within an accuracy of 80.13%. This lower accuracy is obtained for the January storm mainly due to the lack of actual roadway closure data.

The findings of the study evidence that the resilience of a system is not an isolated issue, on the contrary, depends on the resilience of other systems that work as a whole within an urban infrastructure. That is, there exists an interdependence between different infrastructure components such as power and roadway networks, which compels adoption of the Co-resilience concept proposed in this study. From policy and planning perspective, Co-resilience concept can aid officials and decision makers in demonstrating the importance of holistic approaches while building a resilient infrastructure which is crucial for communities to withstand against and rapidly recover from extreme weather events. From a more practical point of view, the proposed models for prediction of roadway closures and power outages and the utilized causality approach can assist city officials during response and recovery phases after extreme events. That is, we showed that power outage information, along with other predictors, can be used to predict the high roadway closure probability throughout the city. This is very important since there is no other option than seek-and-find or citizen-reporting to locate roadway closures and send crews to fix the problem. However, using the prediction approach presented in this study, critical locations with high probability of roadway closures can be identified, and public work crews can be directed to those critical locations.

In general, the addition of the proposed multi-network co-resilience framework into the electric grid outage management brings more situational awareness and helps in a more effective emergency management planning for city governments, electric utilities, transportation departments, and other stakeholders. As such, the findings of this paper can help policymakers in developing methodologies to come up with the multi-network and multi-domain solutions for their infrastructure resilience problems. Future work is directed towards enhancing Co-Resilience metric with the inclusion of other infrastructure networks. Furthermore, this method will be applied on larger data sets and case studies to yield better insights regarding the model performance.

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