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Multi-Dimensional Infrastructure Resilience Modeling: An Application to Hurricane-Prone Electric Power Distribution Systems

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***Abstract*—Despite the scientific consensus on the multivariate nature of resilience, the majority of the existing approaches either focus on modeling a single dimension of resilience, or model its various dimensions separately. In this paper, we propose leveraging one of the most recent advances in statistical machine learning to characterize the multivariate inoperability of an electric power distribution system as a non-linear function of the system's topology, hurricane hazard characteristics, as well as the service area's climate and topography. The model can then be used as a predictive tool to assess various investment strategies for enhancing the multivariate resilience of the system. The results established the number of customers served, tree-trimming frequency, hurricane intensity, land-cover types and soil moisture as the key predictors of the distribution system's multivariate inoperability. The variable influence heat-map helped identify the clusters of predictors that jointly influence one or more measures of inoperability. Moreover, the partial dependence plots were leveraged to examine the non-linear relationships between the focal predictors and the various measures of hurricane impact. The estimated multivariate inoperability model was then used to assess resilience enhancement strategies. The proposed approach can help infrastructure managers and urban planners to approximate the multivariate resilience of infrastructure holistically, predict the system's resilience under various stochastic perturbation regimes, and identify effective strategies to improve the overall resilience of the system.**

***Index Terms*—Infrastructure resilience analytics, hurricane-induced outages, multi-dimensional resilience modeling, multivariate resilience.**

I. Introduction

The U.S. critical infrastructure and the communities that rely on their services are exceedingly more vulnerable to climatic shocks [1, 2]. The need for accurate and holistic disaster resilience modeling has been brought back to the limelight following the recent devastations by hurricanes Harvey, Irma, Jose and Maria that have crippled many communities in the U.S. and the Caribbean Islands. The expansive power outages in the aftermath of Hurricane Maria in Puerto Rico, which left much of the island in the dark and constrained their access to clean water, have had dire economic repercussions and adversely affected the public health and social well-being of many residents in Puerto Rico. Mountains of debris still remaining months after the impacts of hurricanes Irma and Harvey in Florida and Texas has negatively affected the business continuity and public health of many communities in these affected regions. These recent devastations call for a paradigm shift to a more holistic conceptualization of disaster resilience in order to foster improved adaptive capacity in the affected communities.

Resilience engineering is an emerging field, concerned with conceptualizing infrastructure performance and assessing system inoperability during and after perturbations and shocks such as climate hazards [3–5]. Accurate and holistic conceptualization of infrastructure resilience can facilitate proactive preparation, response and mitigation planning. It can therefore strengthen and accelerate infrastructure recovery, foster graceful degradation against hazards, and minimize the large-scale social costs that are typical of natural hazard impacts.

According to the National Academy of Sciences (NAS), disaster resilience is defined as "the ability to plan and prepare for, absorb, recover from, and adapt to adverse events" [6]. As stated by Linkov *et al.* [7] "resilience, as a property of a system, must transition from just a buzzword to an operational paradigm for system management, especially under climate change." Despite much progress in conceptualizing resilience, significant knowledge gaps remain [8, 9]. These gaps are rooted in "the failure to recognize the necessity of a pluralistic understanding of resilience that limits the perspective of many scholars working in resilience research" [10]. Despite the consensus on the multivariate nature of resilience in the scientific community [11–15], many of the infrastructure resilience models focus on estimating a single—often technical—dimension of resilience. For example, many approaches involve modeling a *single* performance measure such as the number of the protective devices activated during disaster impacts (e.g., [16–19]), the duration of loss of service (e.g., [20, 21]) and the fraction of customers without power (e.g., [22–24]). More recently, it has been suggested to include the stress dimension in resilience assessment to mimic the conceptualization of resilience in material science [25]. The more 'holistic', *multi-dimensional* conceptualization of resilience that also includes other important dimensions such as social and economic factors is either based on aggregating multiple resilience indicators [26] which fall short of capturing the dynamic nature of resilience, or involves modeling the various dimensions of resilience separately [12] which could under-estimate the synergies between different dimensions of resilience.

To address the gaps identified above, we propose a novel empirical framework to conceptualize the multivariate resilience of an infrastructure system. Considering that "re-

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silience is better understood as the outcome of a process that includes: sensing, learning, anticipation, and adaptation [9]", we illustrate how various types of data (i.e.,'sensing') can be leveraged to estimate the multivariate inoperability of an infrastructure system as a function of the system's topology, hazard characteristics and other environmental conditions (i.e.,'learning'). The model can then be used as a predictive tool to best prepare for and response to future climate hazards (i.e.,'anticipating'). Moreover, the model can be used to simulate 'what-if' scenarios to identify strategies for enhancing the resilience of the system (i.e.,'adaptation').

To illustrate the applicability of the proposed approach, data from Hurricane Katrina's impact on an electric power distribution system located in the Central Gulf Coast Region of the U.S. were used. More specifically, a recently developed multivariate, ensemble, tree boosting algorithm was leveraged to (a) simultaneously estimate the spatial distribution of the number of electric power outages, the number of customers without power and the cumulative length of power restoration, and (b) establish the cluster of focal variables that are critical for approximating the multivariate resilience manifold.

The structure of this paper is as follows. The motivation behind conducting multi-dimensional infrastructure resilience modeling is expanded upon in Section II. The data and methods are described in Section III. The results are delineated in Section IV, followed by a summary of the concluding remarks in Section V.

II. Background

Reliable provision of services such as energy, water and mobility, supplied through critical infrastructure, is essential for ensuring the national security and sustaining the economic productivity and social well-being of every society. The U.S. critical infrastructure is increasingly prone to climatic risks that cause billions of dollars in losses annually [27]. For example, the electric disturbance event data (OE-417) collected by the Department of Energy revealed that severe climate events were among the most frequent cause of power outages in the U.S. since the early 2000's [28, 29]. Due to the increased vulnerability of our infrastructure to climate extremes, resilience has gained national attention in recent times [6, 30]. Significant research progress has been made in modeling infrastructure resilience. The existing approaches can be categorized as: (a) conceptual and analytical techniques [1, 4, 31]; (b) hazard and impact simulation [23, 32, 33]; (c) system optimization [1, 34–37]; (d) probabilistic risk analysis [12, 25, 38–40]; (e) statistical methods and machine learning algorithms [20, 22, 24, 41–44]; (f) robust decision-making under uncertainty [45–49]; (g) input-output modeling [50, 51]; and (h) network-based approaches and graph theory [52–55].

While the existing approaches have contributed to our capability to support resilience enhancement decisions, fundamental research gaps remain. More specifically, the existing infrastructure resilience models either (a) characterize a single—often technical—dimension of resilience (e.g., modeling the recovery of interrupted service by [20, 21, 56, 57]); rendering them unsuitable for *multi*-dimensional analysis of the resilience metrics and integrating other (e.g., social) dimensions of resilience [58], or (b) model the various dimension of resilience separately (e.g., [12]); which, while helpful in providing a pluralistic understanding of the resilience of the system, fall short of characterizing the potential synergies and interactions between the different dimensions of resilience.

To address these gaps, we propose leveraging a data-driven, multivariate analysis to model the complex interplay between stochastic hazards, system topology, and the topography of the region and accurately approximate the multi-dimensional resilience manifold over the high-dimensional parameter space that characterizes the entire system of interest. Since operationalizing resilience hinges on identifying "the resilience of what, to what, and for whom" [59], and requires clear systems boundaries, we will assess the resilience of a power distribution system to hurricanes from the perspective of the state utility commission and the utility company serving the region. While we leverage data from an electric power distribution system impacted by hurricane Katrina as a case study, in the presence of adequate data, the approach can be extended to any other type of urban infrastructure impacted by hydro-meteorological hazards. The central thesis in this paper is that leveraging a *multivariate* approach that allows for simultaneous estimation of the joint spatial distribution of the various quantitative measure of inoperability—as a (non-linear) function of hazard characteristics, system's topology, and the region's land-cover and topography—can facilitate a more holistic characterization of a system's resilience and thus can motivate more effective investment prioritization schemes.

III. Data and Methods

A. Data

Previous literature has established a wide range of variables that are necessary for estimating electric power outage risks and resilience due to extreme weather and climate events [2, 17, 20–22, 60, 61]. The data used in this paper were provided by an electric utility company that serves the central Gulf Coast region of the U.S. The electric utility's service area consists of 6,681 grid cells with dimension of 12,000×8,000 ft (3.66×2.44 km). The service area under study was heavily impacted by Hurricane Katrina, with more than 80% of the customers affected and outage restorations taking up to 12 days.

The categories of the input data used in the analysis are summarized in Table I. The first three rows in Table I represent the multivariate response. More specifically, outage duration represents the cumulative sum of the duration of power outage restorations (in minutes). Outage counts refer to the number of protective devices that were activated and led to non-transitory (i.e., < 5 minutes) loss of power. The number of customers affected refers to the number of customer meters that lost power during Hurricane Katrina.

The independent variables used in this analysis comprise of sixty-three covariates that characterize the hurricane hazards, the topology of the system as well as the topography, climate and land-cover of the service area. To characterize the intensity of the hurricane, the Willoughby's parametric wind-filed model [62, 63] was used to estimate the 3-second gust wind speeds and the durations of winds (in minutes) blowing above 20 ms^{-1} at the centroid of each grid cell. The threshold of 20 ms^{-1} is based on the design wind-load of the utility poles in the service area [20]. The tree-trimming metric represents a length-weighted time since last clearing for a given grid-cell, with larger values indicating less frequent tree-trimming [2]. Details of the number of poles, transformers, switches, relays, re-closers as well as miles of overhead and underground lines, as well as the number of customers served in each grid-cell were provided by the utility company. The topography of the service area was characterized by various statistics associated with the elevation, aspect ratio and slope of the terrain. Compound topographical index (CTI)—a measure of relative wetness of a particular region—as well as soil-type and soil moisture anomaly (the day before the hurricane's landfall, at various depths of 0-10 cm, 10-40 cm, 40-clay) were also included in the analysis. As suggested by [64] standardized precipitation index (SPI)—a statistical measure of precipitation deviations from normal conditions—for six different lagged times of 1, 2 , 3 , 6 , 12 and 24 months, were used. The SPI index was used as a proxy for the drought or wetness conditions of the region. The mean annual precipitation (MAP) in each grid-cell was used as a proxy for latitudinal diversity gradient [20, 65]. Various types of land cover were also included in the analysis in order to take into account the differences in power outage risks in different land-uses [66]. The land cover data used in the analysis is available from the National Land Cover Database (NLCD) 2001. The NLCD's 21 types of land cover were aggregated into the following eight classes of:

1) water: open water or areas with permanent ice/snow cover;
2) developed: including residential, commercial, and industrial areas;
   The developed area is partitioned based on the intensity of development. The lowest intensity development is open space with impervious cover below 20% (e.g., parks and golf courses). The low intensity development has impervious cover in the range of 20-49% (e.g., single-family housing). The medium intensity development has higher impervious cover in the range of 50-70%. The high intensity development has impervious cover above 80% (e.g., apartment complexes, commercial or industrial complexes). The percentage cover development for each class of land cover was calculated at the grid cell level and included into the analysis.
3) barren: areas covered by rock, sand and silt with minimal vegetation cover;
4) forest: areas covered with trees taller than 6 meters;
5) shrub-lands: covered with woody vegetation and trees shorter than 6 meters;
6) grass: areas dominated by herbaceous vegetation that are not subjected to intensive landscaping management;
7) cultivated: areas subjected to intensive management such as pastures or cultivated crops;
8) wetland: areas with soil that is saturated or covered with water.

TABLE I: Summary of the input data

Variable	Description
Outage Duration	Cumulative duration (mins) of restoration
Outage Counts	No. of protective devices activated leading to non-transitory loss of power
Customers Affected	No. of customer meters without power
Wind Speed	3-seconds wind gusts (ms^{-1})
Wind Duration	Duration (mins) of winds above 20 ms^{-1}
Tree Trimming	Length-weighted time since last trimming
Protective devices	No. of poles, switches and transformers
Overhead	Miles of overhead lines
Aspect Ratio	Min, Max, $\bar{x}$, $\hat{\sigma}$ of the land's aspect ratio
Elevation	Min, Max, $\bar{x}$, $\hat{\sigma}$ of the land's elevation
Slope	Min,Max, $\bar{x}$, $\hat{\sigma}$ of the slope of the land
MAP	Mean annual precipitation
SPI	Standardized precipitation index
CTI	Compound topographic index
Soil	Soil moisture *prior to* a hurricane landfall, soil type, and soil clay content
Land cover	Water, barren, forest, shrub, pasture, wetland, developed

TABLE II: Summary statistics of the multivariate response

Response Variable	Mean	Skewness	Kurtosis
No. of Customers Affected	90.0	8.6	96.6
Outage Duration	3082.0	7.7	77.9
Outage Counts	78.0	6.7	63.6

The summary statistics of the multivariate response, i.e., the duration and number of outages, as well as the number of customers without power are summarized in Table II.

All of the three response variables are right-skewed, with the number of customers without power more heavy-tailed than the other variables.

B. Data-driven, Multi-dimensional Resilience Modeling

We propose leveraging one of the most recent advancements in the field of supervised learning theory to spatially estimate the joint distribution of various dimensions of resilience as a (non-linear) function of hazard characteristics, system topology and the area's climate, land-cover and topography. In this section, we first provide a theoretical grounding in the general area of supervised learning, and then focus on introducing ensemble, tree-based learning methods. The introduction will be followed by a brief description of the recent multivariate extension of ensemble tree boosting that was leveraged in this paper. The section will close by summarizing the proposed data-driven, multi-dimensional resilience modeling approach.

1) Theoretical Background Information: Supervised learning has been extensively used in the areas of infrastructure risk, reliability and resilience modeling [2, 18, 21, 22, 24, 28, 67–71].

Mathematically, supervised learning can be described as: $\mathbf{y} = \mathbf{f}(\mathbf{X}) + \epsilon$ where $\mathbf{y}$ represents the process of interest; $\mathbf{X}$ represents the of input variables used to approximate the response function; and the stochastic, additive noise ϵ is referred to as irreducible error. The goal of supervised learning is to leverage data and approximate the response surface such that the loss function of interest $\mathbf{L}$ is minimized over the domain of the input space $\mathbf{X}$ [72–74].

$$\mathbf{L} = \int_D \omega(X)\mathbf{\Delta}[\hat{f}(\mathbf{X}), f(\mathbf{X})]d\mathbf{X} \tag{1}$$

where ω represents a weight function and $\mathbf{\Delta}$ represents some measure of distance (e.g., Euclidean or Mahalanobis distance) [73, 74].

label=–

- *Parametric versus Non-Parametric Supervised Learning Methods:*

Supervised learning algorithms range widely in their degree of complexity and flexibility and can be either parametric or non-parametric. The most popular approach is parametric modeling (e.g., generalized linear regression) where a parametric function is fitted to the data (e.g., via least-squares), such that: $\hat{f}(\mathbf{X}) = g(\mathbf{X}|\{\hat{\beta}_j\}_1^p)$. The advantage of parametric modeling is that by assuming a functional form, the problem of estimating the complex response function is reduced to estimating a set of β parameters, which renders the method simple to compute and interpret. However, such an approach is 'rigid', and its limited flexibility means that it often fails to approximate the true function accurately.

On the other hand, non-parametric models such as artificial neural networks, support vector machines, and tree-based algorithms do not make assumptions about the shape of the function. Instead, they use data in novel ways to approximate it. While they have the advantage of not assuming unrealistic functional form and thereby better approximating the true function, they can be very data-intensive.

label=–

- *Tree-based Algorithms:*

One class of non-parametric algorithms that has been widely popular in infrastructure risk and resilience analysis is *ensemble tree-based methods* [16, 18, 20, 22, 64, 67]. Tee-based methods are widely popular because while they are competitive, in-terms of predictive accuracy, with many of the of state-of-the-art algorithms [75], the lend themselves more easily to interpretation and statistical inferencing when compared to 'black-box' methods such as artificial neural networks and support vector machines [74].

Tree-based data-miners (e.g., CART) are 'learned' by splitting the data space recursively into nodes [74]. Mathematically, they can be represented by the following piecewise function:

$$F(\mathbf{X}) = \sum\nolimits_{j=1}^{J} \lambda_j I(\mathbf{X} \in R_j) \tag{2}$$

where the predictors split the data recursively into R_j regions, and λ_j is the prediction in each region [74]. The indicator function $I(\mathbf{X} \in R_j)$ identifies which observations in $\mathbf{X}$ belong to region R_j. Therefore, the tree $T(\mathbf{X})$ is a piecewise approximation of the unknown, but complex response function $F(\mathbf{X})$. To avoid over-fitting, the grown tree is "pruned' back based on a "cost-complexity criterion" [76]. In addition to accounting for non-linearities and interactions, decision tree-based algorithms can impute missing values in the data using a procedure called "surrogate splitting" [74]. In the presence of missing values in the splitting variable, a "surrogate" variable is identified and selected that best approximates the original split value. Individual observations with missing values are then modeled according to the split on the surrogate rather than the original splitting variable. label=–

- *Tree Ensembles:*

Meta-algorithms such as "boosting' and "bagging' can be applied to tree algorithms to create *ensembles* [74]. Tree-ensembles are robust to outliers and noise [74]. They often exhibit superior predictive accuracy compared to most other state-of-the-art statistical and machine-learning algorithms [2, 18, 20, 67, 75], rendering them an ideal approach for infrastructure risk, reliability, and resilience analysis. In bagging (aka bootstrap aggregating) multiple trees are built using bootstrap samples of the training data, and the prediction of the ensemble is the average of predictions across all trees. Bagging reduces the prediction error by decreasing variance and minimizing the influence of outliers. Boosting, on the other hand, builds a tree ensemble by fitting trees that incrementally enhance the predictive accuracy of the model. More specifically, boosting involves iteratively creating an ensemble of trees such that in each iteration a greater weight is given to the observations that have been poorly predicted in previous trees [77]. In other words, the subsequent trees boost the performance of the overall model by selecting predictor variables and split values that better estimate the observations that are most poorly predicted. This procedure of iteratively fitting decision trees to the poorly predicted observations has been demonstrated to be equivalent to estimating an additive model of decision trees via the gradient descent algorithm [74, 78] as shown below:

$$\mathbf{y} = F(\mathbf{X}) = \sum\nolimits_{m=1}^{M} T_m(\mathbf{X}, \theta_m)\nu \tag{3}$$

Where $F(\mathbf{X})$ is approximated using the additive model of $m = 1, \ldots M$ trees. Since there is no closed form solution for estimating the parameters θ_m simultaneously across all trees, the gradient descent algorithm is often used for parameter estimation. In other words, the parameters are estimated by fitting each tree to the first derivative of the loss function (i.e., the gradient) [79]. Each tree m has split variables θ_m and values of ν represents the step-size and controls how quickly the model fits the observed data. The size and depth of the trees, and the step-size ν are meta-parameters that regulate the complexity of the ensemble model, and are typically tuned based on out-of-sample cross-validation.

2) Multivariate, Tree Boosting: The approach leveraged in this paper is based on a recently developed multivariate tree boosting algorithm [78] which allows for identifying the key predictors of the multivariate response manifold with non-linear effects and interactions. Multivariate tree boosting algorithm also facilitates selecting predictors that account for the covariance between the pairs of response variables; which can be implemented by maximizing the *covariance discrepancy (D)* at each gradient descent step in growing trees. Maximizing D directly corresponds to selecting predictors that account for the covariance in the multivariate response.

The covariance discrepancy can be mathematically represented as:

$$D_{m,r} = ||\hat{\mathbf{\Sigma}}_{(m-1)} - \hat{\mathbf{\Sigma}}_{(m,r)}|| \tag{4}$$

where D measures the discrepancy between the sample covariance matrix of the response variables at the previous step $\hat{\Sigma}_{(m-1)}$, and the sample covariance matrix at step m, $\hat{\Sigma}_{(m,r)}$, after training a tree to the response variable $y^{(r)}$. At the first step, the sample covariance matrix is: $\hat{\Sigma}_{(0)} = S$. It can be inferred that $D_{m,r}$ measures the amount of covariance explained in the multivariate response by the predictors selected to fit the tree to $y^{(r)}$ in step m. D therefore, measures the improvement in how well the model fits the sample covariance matrix at each iteration. The multivariate ensemble tree boosting algorithm is summarized below:

Algorithm 1 Multivariate Ensemble Tree Boosting, using Covariance Discrepancy D [78]

```
1: for m in 1,...,M steps (trees) do
2:     for r in 1,...,R quantitative response variables do
3:         train tree m^(r) to residuals, and estimate the covari-
           ance discrepancy D_{m,r} (equation 4)
4:     end for
5:     Select the response y^(r) corresponding to the tree that
       yielded the maximum D_{m,r} (equation 4)
6:     Update residuals by subtracting the predictions of the
       tree fitted to y^(r), multiplied by step-size.
7: end for
```

In the first iteration (i.e., $m = 1$), the model predictions are set to the average values of the response variables, and the residuals are estimated by measuring the deviations of the response variables from their average values. The trees are estimated for each response variable by minimizing the $L2$-norm (i.e., the squared error loss). At each gradient descent iteration m, one tree is chosen whose selected predictors lead to maximized covariance discrepancy (equation 4).

The optimal number of the tree ensemble is selected based on cross-validation. More specifically, the number of trees that lead to the minimum mean squared error (shown below) will be selected:

$$MSE = \frac{1}{nR}\sum\nolimits_{i=1}^{n}(\mathbf{Y}_i - \hat{\mathbf{Y}}_i)^2 \tag{5}$$

where $\mathbf{Y}_i$ is the vector of observations in each grid-cell $i = 1, \ldots, n$ that were not used in the training the model for R response variables and $\hat{\mathbf{Y}}_i$ is the predicted values based on the multivariate boosted trees.

Inferences for the multi-dimensional models developed using the multivariate tree boosting algorithm can be made based on the following metrics of: (1) measuring the relative influence of each predictor on individual outcome variables, and identifying the clusters of predictors that jointly influence one or more response variables; (2) visualizing the partial dependence between the predictors and the outcome variables; and (3) detecting predictors with potential non-linear effects. Each of these metrics will be briefly discussed below:

label=–

- *Variable selection based on relative influence of individual predictors:*

For ensemble, tree-based methods, the relative influence of a given predictor is characterized by measuring the sum of squared error due to any split on that predictor, summed over all trees in the the prediction model [74, 80]. The calculated sums of squared errors help rank the independent variables according to their relative influence, which is often reported as a percent of the total reductions in error attributed to all predictors. In the case of multivariate response variables, the univariate relative influence is first calculated for each predictor and for each of the response variables. Summing the importance over all response variables establishes a global measure of importance for the predictor across all response variables. Moreover, to help with the multivariate, tree-based modeling inferences, the predictors can be grouped using clustering techniques. More specifically, The relative influence measures can be clustered by first calculating the distance (e.g., Euclidean or Manhattan distance) between columns (i.e., the predictors) and the rows (i.e., pairs of response variables), respectively. Predictors that explain similar patterns of covariance in the response variables will be closer to one another as will pairs of response variables that are functions of a similar subset of predictor variables. The calculated distance matrices can be used to group the predictors that explain covariance in similar pairs of response variables, and the pairs of responses that are dependent on similar subsets of predictors by hierarchical clustering technique [78, 81].

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- *Visualizing the partial dependence between the predictors and the response variables:*

Partial Dependence Plots (PDP) [74, 82] are usually leveraged to make statistical inferences based on non-parametric models such as ensemble tree-based methods. The partial dependence between the multivariate response and the input variable of interest can be calculated using the following equation [74].

$$f_j(x_j) = E_{x_{-j}}[f(x_j, x_{-j})] = \int f(x_j, x_{-j})dP(x_{-j}) \tag{6}$$

The estimated PDP provides the average value of the response function where all other input variables are accounted for, and varies over its marginal distribution.

label=–

- *Detecting predictors with potentially non-linear and non-additive effects:*

In tree-based models, two-way interactions between the input variables can be detected by checking if the estimated values (as a function of the pair of predictors) deviate from the linear combination of the two predictors. Such deviations signal that the joint influence of the predictors is not additive and potentially has a non-linear effect [78, 83]. Significant deviations from additivity can be identified by estimating the response as a function of any pair of predictors, over a grid of all possible levels of the two predictors. The estimated values are then regressed onto the grid. Large residuals resulting from this model would indicate that the estimated values are not a linear combination of the predictors, thereby signaling the presence of non-linearity or interaction effects. For computational simplicity, and in the presence of many predictors, detecting potential non-linearities can be focused on the most important predictors which are identified via calculating the relative influence of the predictors described above.

3) Proposed Approach: The multi-dimensional infrastructure resilience modeling approach is algorithmically summarized below:

Algorithm 2 Data-driven, Multivariate, Resilience Modeling Approach

for a given hazard environment **do**
  identify the multivariate measures of system inoperability
  collect relevant data
  leverage Algorithm 1 (Section III-B2) to estimate the multivariate inoperability measures as a function the input parameter space
  asses model accuracy and create spatial visualization
  if accuracy $>$ acceptable threshold set by the stakeholder (e.g., errors $< 10\%$) **then**
    identify the key predictors of the multivariate inoperability and plot heat-maps
    asses the (non-linear) influence of the key predictors on the multivariate response through partial dependence plots
  else
    improve data collection, further model tuning
  end if
end for
generate credible resilience investment scenarios
for Scenarios $s \ in \ 1 \ \ldots \ S$ **do**
  run the multivariate algorithm and calculate %improvement in the multivariate resilience
end for
identify the non-dominated solution(s)

The approach warrants direct engagement with stakeholders to identify the relevant resilience metrics and acceptable accuracy thresholds. The implementation of the proposed approach is presented in the next section.

IV. Results

An ensemble of boosted, multivariate trees was trained with the data described in Section III-A. The multivariate response variables include (1) the cumulative duration of outages, (2) the number of customer meters without power, and (3) the number of outages (i.e., the number of protective devices activated, leading to non-transitory loss of power). In building each of the trees in the ensemble model, 50% bootstrap sample of the data were used to train the multivariate model and the remaining 50% holdout sample was used to estimate the predictive accuracy. The optimal number of multivariate trees were selected based on five-fold cross-validation [74]; which suggested 435 trees would yield the lowest out-of-sample prediction error.

As discussed earlier in Section III-B, the goal of supervised learning is to leverage data to best approximate the response surface; and the performance of a trained supervised learner is typically assessed by measuring how much the predictions deviate from the observed data (e.g., via mean absolute deviation and/or mean squared error) [74]. The performance of the multivariate model in predicting each of the response variables is summarized in Table III. The table shows the mean squared error (MSE), and the mean absolute deviation (MAE) associated with the model's prediction as well as the error associated with a null (aka 'mean-only' model); where the mean of the response is used instead of a statistical model. In statistical analyses, the null model is used as a benchmark to assess the degree to which a statistical model is capable of prediction beyond it's historical average. It can be seen that the multivariate, ensemble model is a substantial improvement over the null model and the difference between the errors associated with the multivariate and null models are statistically significant (based on the results of non-parametric sign-tests with p-values $< 2.2 \times 10^{-16}$ for all pairs of error vectors).

TABLE III: Model Performance

Variable	Model	MSE	MAE
Outage Duration	Multivariate Model	0.28	0.22
	Null Model	0.42	0.99
No. of Customers-out	Multivariate Model	0.27	0.18
	Null Model	0.38	0.99
Outage Counts	Multivariate Model	0.22	0.23
	Null Model	0.47	0.99

It can also be observed from Figure 1 that the multivariate model yields reasonable fit to the data. The correlations between the predicted and observed values are: 85% for the cumulative outage durations, 86% for the number of customer-meters out, and 88% for the number of outages. Note that the outcome variables were standardized to avoid biased variable selection due to different scales in the multivariate response.

Figure 2 visualizes the spatial distribution of the model's errors in the region of interest. Note that the state and county boundaries are not depicted to keep the region under study anonymous. It can be seen that the percentage error in most areas are below 10%. The red squares represent over-prediction and the blue squares represent under-prediction. The map reveals that the model tends to over-predict in urban areas and under-predict in rural communities. Moreover, the few grid-cells with percentage errors higher than 10% tend to be primarily in urban regions. We hypothesize that adding other attributes that can help capture the structural differences between rural and urban counties may help improve the model's performance.

Figure 3 depicts the heat-map of the relative variable influence for the most important predictors which were selected and ranked based on their contribution to the out-of-sample accuracy of the multivariate model. The heat-map is a useful visualization tool since it also leverages hierarchical clustering to group the most important predictors that explain similar patterns in the covariance of the response manifold. Inspecting Figure 3 reveals that the number of customers served in each grid-cell, and the utility company's tree-trimming frequency are the most important predictors of the multivariate inoperability measure. The association between the number of customers and the multivariate response is intuitive, since a larger number of customers indicates a higher extent of the vulnerability of the system to (climate) hazards. Moreover,

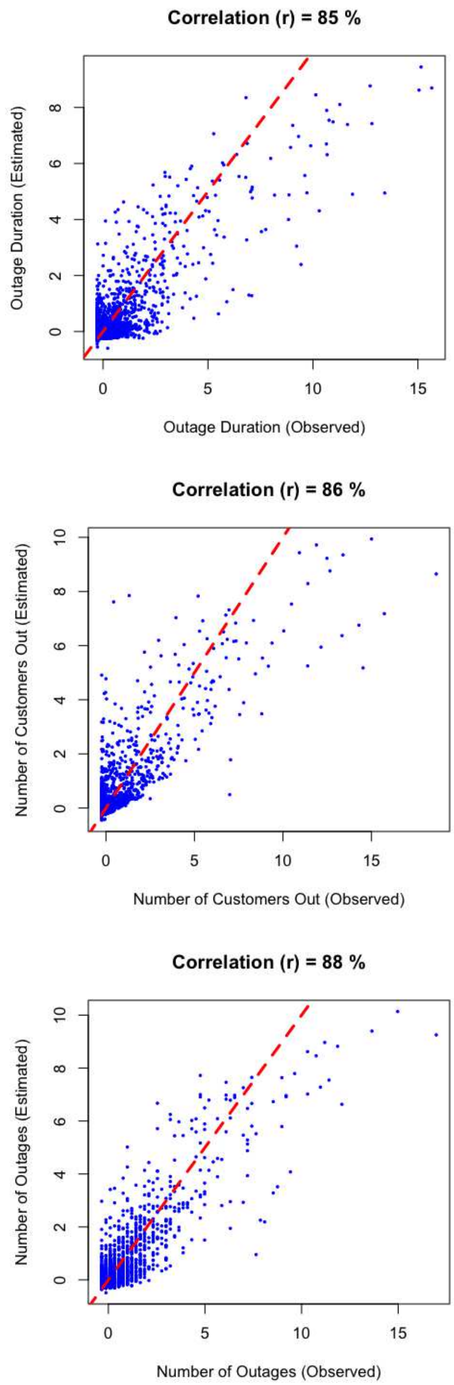

Fig. 1: Visualization of model performance

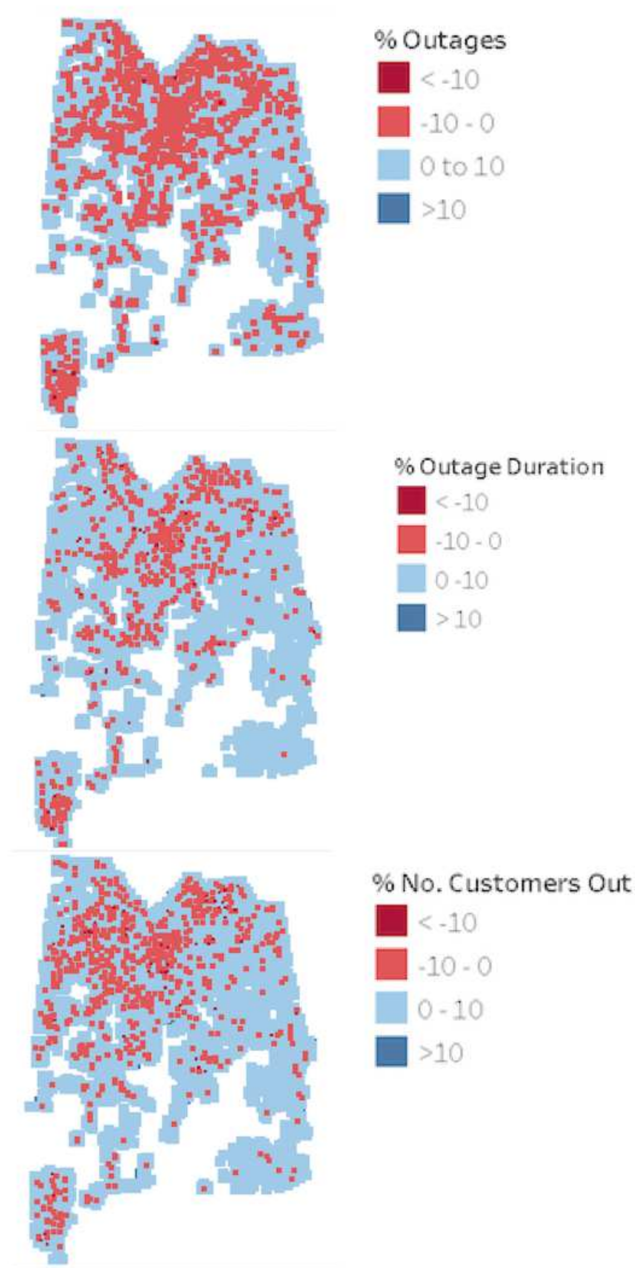

Fig. 2: Spatial visualization of model's performance. The areas in red represent over-prediction and the blue areas represent under-prediction

identification of trimming cycles as the key predictor is consistent with the previous research [16, 40, 84] that established trees as the key predictor of storm-induced damage. Figure 3 also reveals that the number of customers is most predictive of the number of customer-meters without power (with a relative importance of 54.3), and that the trimming frequency is most predictive of the number of outages (with a relative importance of 20.5). The measures of hurricanes intensity (i.e., wind-gusts and durations of strong winds) are more predictive of the duration of recovery as opposed to the number of outages and customer-meters out. This is expected since more intense hurricanes are associated with higher likelihoods of damaged assets which may need to be replaced and therefore cause longer recovery rates. Figure 3 also shows that while various types of land-cover (e.g., low, medium and high development areas) are more predictive of the number of customers without power, the service area's climate and topography (e.g., minimum and maximum elevation, standardized precipitation index, saturated soil and standard deviation of the compound topographic index) are more predictive of outage duration. This finding is consistent with the anecdotal experiences of post-disaster responders, as the area's topography (e.g.,

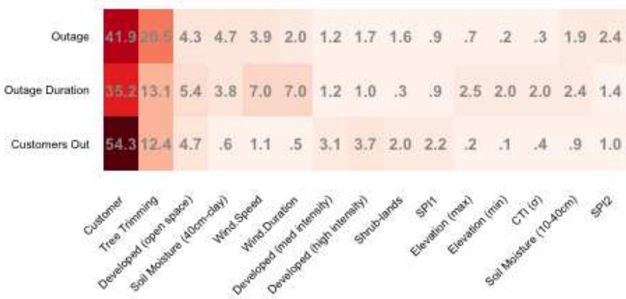

Fig. 3: Variable Influence

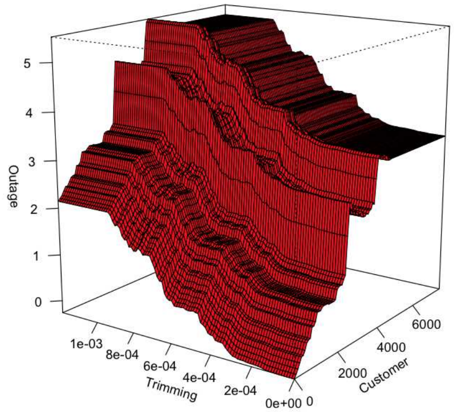

Fig. 4: Partial dependence plot of the number of outages versus trimming cycles index and the number of customers served

elevation) and level of soil saturation can hamper the response crew's access to the heavily impacted areas. The importance of land-cover types in predicting the multivariate response is not surprising. Developed open spaces and medium intensity developments are generally associated with suburban neighborhoods, while the high intensity developed areas are associated with urban regions; all of which are endowed with a relatively high presence of electric power distribution system assets. Developed land-cover type, therefore, serves as proxy variables for the varying degree of the vulnerability of the electric power infrastructure system in these areas.

To examine the (non-linear) influence of the most important predictors on the inoperability measure, partial dependencies were plotted. The functional form of the partial dependence of each of the response variables on the tree-trimming frequency and the number of customers served in each grid-cell were found to be very similar; differing only in the range of the response values along the z axis. For the sake of brevity, we have plotted the partial dependence of the number of outages on the tree-trimming index and the number of customers served.

Figure 4 reveals that higher numbers of customers and less frequent tree-trimming (i.e., the higher values of the trimming index) are both associated with more outages. The small dip in Figure 4 for the number of customers between 2000–4000 and the plateau after a threshold of 6000 customers can be attributed to more developed urban areas with mostly

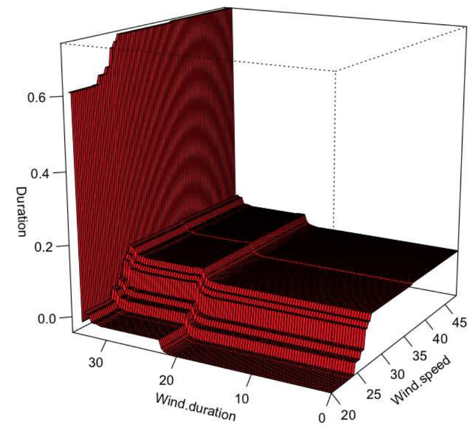

Fig. 5: Partial dependence plot of outage durations versus duration of strong winds and 3-second gust wind-speed

under-grounded power distribution systems that tend to be less vulnerable to storm impacts.

Plotting the hurricane intensity versus the cumulative duration of recovery reveals interesting threshold effects that are critical in engineering resilience modeling. Figure 5 reveals that experiencing wind-gusts of over 25 ms^{-1} and strong winds blowing over 30 minutes are associated with a significant step-function increase in outage duration. This result has very important implications, particularly for the resilience engineering community which assesses the fragility of power systems assets as a function of peak winds alone, and does not account for the durations of strong winds.

A. *Scenario-based Analysis*

One of the primary goals of applying resilience theory to empirical case studies is to assess the current state of the system and predict the system's inoperability and resilience under (uncertain) perturbations [15]. Such empirical assessments can then be leveraged by stakeholders and decision makers to (1) identify actions that may alter the system's resilience, and (2) identify strategies that focus on enhancing particular priorities such as improving the social equity in addition to ensuring the overall economic prosperity [15]. The model presented earlier in this paper can be used to implement such scenario-based analyses and provide support for decisions to improve the resilience of the system to future impacts.

The variable influence heat-map depicted in Figure 3 indicates that the tree-trimming frequency is a key predictors of the multivariate resilience metric. The decision-makers of the region could potentially contemplate two competing options of either increasing the frequency of tree-trimming in the more densely-vegetated regions or under-grounding the most vulnerable distribution assets in the heavily impacted areas. The analysis helped identify 50 densely-vegetated grid-cells with the least frequent trimming cycles that had rendered the system vulnerable during the hurricane impact. Trimming the trees in these areas—to ensure minimized risk of tree-induced outages—can help significantly shrink the tail of the multivariate outage distribution. Moreover, we identified 5

TABLE IV: Percentage change in inoperability (i.e., the multivariate response manifold) associated with resilience investment scenarios of (1) more frequent tree-trimming, and (2) under-grounding the distribution system in the most vulnerable grid-cells. The percentage reduction has been calculated relative to the baseline (or 'do nothing' scenario)

Scenario	Durations	Customers Out	Outage No.
Tree-Trimming	-68%	-11%	-56%
Under-grounding	-84%	-79%	-65%

adjacent (coastal) grid-cells that were most vulnerable to the hurricane's impact. Under-grounding these 5 grid-cells could also mitigate the impact of the hurricane. More specifically, running the multivariate prediction model for the two hypothetical resilience investment scenarios of: 1) more aggressive and frequent trimming of the trees in the identified grid-cells and 2) under-grounding the most vulnerable sections of the distribution system in 5 (coastal) grid cells can help assess the potential alleviating effects of each scenario under a future hurricane impact with similar hazard characteristics to Katrina. The results are summarized in Table IV. It can be seen that under-grounding only 5 grid-cells can be more effective in mitigating the hurricane impacts than frequent tree-trimming in 50 grid-cells. The results also suggest that while a more frequent tree-trimming strategy can be compelling, it will be more effective for reducing the number and duration of outages and will be a less effective measure for reducing the number of customers without power.

Under constrained resources, the optimal resilience investment decision will be based on the least cost solution which has the maximum benefit in-terms of reduced overall impacts. Additional information about the cost of under-grounding the vulnerable coastal region of around 42 km^2 versus conducting a more frequent tree-trimming in an area of about 432 km^2, and also further knowledge of the types of customers who will experience reduced outages and their concomitant value of lost load (VOLL) estimates [1] can help make such critical resource allocation decisions. A similar analysis could also be implemented for an ensemble of simulated hurricanes, with varying intensities, to compare how the resilience of the system would differ under stronger or weaker storms.

V. Conclusion

Infrastructure resilience is an emerging area of research which is concerned with conceptualizing and measuring the performance and inoperability of critical systems during and after the impact of extreme events. Despite the scientific consensus on the multifaceted nature of the resilience, the majority of the existing efforts in the engineering community treat resilience as a $1-$dimensional concept, and implement univariate analysis to characterize the resilience of the system of interest. In this paper, we propose leveraging a data-driven, multivariate framework to characterize the multi-dimensional resilience of a system. The proposed framework allows for establishing the clusters of focal variables that are critical for estimating the multivariate resilience manifold. Approximating the multivariate resilience, combined with a scenario-based approach—for considering alternative future risk-mitigation investment strategies—provide a powerful surrogate model of the current state of resilience of the system which can help characterize the likelihood of change in the multivariate resilience under specified systems conditions and stochastic perturbation regimes.

We conducted the empirical multivariate resilience analysis for a power distribution system impacted by Hurricane Katrina. The model allowed for simultaneously predicting the spatial distribution of the number of outages, the number of customers without power and the total cumulative outage durations at each grid-cell with reasonable accuracy. Moreover, the model helped identify the clusters of focal variables such as the number of customers served, tree-trimming cycles, land-cover types and soil moisture levels that are key to explaining the covariance of the multivariate response. The developed model can adequately capture the non-linear dependencies and the hierarchical structure of the data. Subject to data availability, the proposed multi-dimensional resilience modeling approach can be easily extended to account for other (quantitative) resilience metrics of interest. This type of analysis allows the decision makers to understand the key factors in determining the multivariate resilience of the system, and can be a powerful tool for assessing the effectiveness of alternative investment decisions in improving the various dimensions of the resilience of the system of interest.

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