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ORIGINAL PAPER

Forecasting hurricane-induced power outage durations

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Abstract Accurate estimates of the duration of power outages caused by hurricanes prior to landfall are valuable for utility companies and government agencies that wish to plan and optimize their restoration efforts. Accurate pre-storm estimates are also important information for customers and operators of other infrastructures systems, who rely heavily on electricity. Traditionally, utilities make restoration plans based on managerial judgment and experience. However, skillful outage forecast models are conducive to improved decision-making practices by utilities and can greatly enhance storm preparation and restoration management procedures of power companies and emergency managers. This paper presents a novel statistical approach for estimating power outage durations that is 87 % more accurate than existing models in the literature. The power outage duration models are developed and carefully validated for outages caused by Hurricanes Dennis, Katrina, and Ivan in a central Gulf Coast state. This paper identifies the key variables in predicting hurricane-induced outage durations and their degree of influence on predicting outage restoration for the utility company service area used as our case study.

Keywords Data mining · Hurricanes · Power outages · Random forests · Power restoration

1 Introduction

Hurricanes and storms frequently cause widespread and prolonged power outages in the USA that adversely impact millions of customers, businesses, and other critical

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infrastructures resulting in large economic and social losses. Being able to accurately estimate power outage durations prior to hurricane landfalls is important for planning post-disaster restoration efforts more efficiently. Storm outage management (SOM) is comprised of four stages, namely, damage prediction, crew staging, post-disaster damage assessment, and restoration management (Lubkeman and Julian 2004). Hurricane-induced power outage and damage models have been developed to predict the extent and spatial distribution of power outages and damages prior to hurricane landfalls (Guikema et al. 2010; Guikema 2009; Han et al. 2009a, b; Nateghi et al. 2013). These models can help utilities optimally plan their crew and resource allocations for storm response. Having accurate power outage duration estimates prior to a hurricane landfall can further help with staging crews more efficiently in order to improve the restoration effort, the last stage of SOM. It can also provide valuable input to the managers of other critical infrastructure systems such as water supply and transportation systems to help them plan their restoration process.

This paper has two main objectives. First, we present a method for predicting power outage durations more accurately than the existing models in the literature. Second, we use the developed forecast model to identify the key variables and their extent of influence on power outage durations caused by hurricanes.

2 Background

A wide range of models have been proposed in the literature to estimate the duration of power outages caused by natural disasters such as earthquakes, storms, and hurricanes. These models provide valuable information for implementing post-disaster restoration efforts more effectively. The existing literature is considerably more extensive for earthquakes than high-wind events such as wind storms and hurricanes. However, seismic events are significantly different from high-wind events because earthquakes last for a much shorter period of time, and despite the occurrence of aftershocks, the post-event restoration patterns are more consistent event to event than those associated with high-wind events (Reed et al. 2003).

Brown et al. (1997) implemented a two-stage Monte Carlo simulation to estimate the impacts of storms on power systems reliability. In the first stage, they simulated high-wind conditions of the storm when all the failures tend to occur. In the second stage, they assumed that the high winds had abated, no new faults occurred, and that the crewmembers were only involved with restoration efforts. They also assumed that the failure rate was only a function of the storm's wind speed squared. The mean-time-to-repair was defined to be the failure rate multiplied by the duration of the storm, and the total expected repair time was calculated by multiplying the failure rate by the mean-time-to-repair values. Their study relies on many assumptions and requires detailed information about the power system for its implementation. Moreover, while the analysis is a useful tool for examining the systems sensitivity to design improvements, it cannot be used in a predictive setting.

Zhu et al. (2007) developed a two-stage prediction method to forecast power outages due to different types of storms (classified into six categories based on their temperatures and speed). They first derived an empirical model through fitting an exponential distribution to the historical hourly outage data for each type of storm. They acknowledged that real-time outage pattern could deviate substantially from their empirically fitted curve. They suggested implementing an adaptive forecast method through tracking the outages in real time, comparing them to the estimates from their empirical model and applying an error compensation to get an estimate of the subsequent forecast. In other words, a correction factor would need to be applied based on the difference between the prediction and the real-time storm data at the end of each hour into the storm. Their model relies on being able to track outages in real time accurately, and the prediction errors are sensitive to the error correction factor used. Moreover, while their estimates showed a reasonable correlation to the historical values, they did not test the performance of their model on an independent sample, and therefore, it is unclear whether their model has any predictive power. The model estimates the hourly number of outages from the onset of the storm, but does not provide the spatial distribution of outages. While the average of number of outages is valuable information for utilities, not knowing the outage locations would hamper storm management efforts.

Liu et al. (2007) used the method of survival analysis to model power outage restoration times for ice storms and hurricanes. They used both accelerated failure time (AFT) and Cox proportional hazard (CPH) regression techniques to predict outage duration times. They recommended using AFT models over CPH models because the results from the CPH models were harder to interpret. They did not implement out-of-sample validation tests to assess the predictive power of their proposed model.

Reed (2008) used a combined statistical–GIS methodology to study the performance of an urban distribution system located in the U.S. Pacific Northwest that was affected by four winter storms. The data logs of the repair crews were plotted in GIS to study outage duration, fragilities, and restoration. To predict reliability indices such as System Average Interruption Index (SAIDI) and System Average Frequency Index (SAIFI) for a selected storm, denoted as STAIDI and STAIFI, they fitted linear regression models to the storm data and reported their associated R^2 values as a measure of their goodness-of-fit. They concluded that gust wind speeds are the best predictor. Their fragility model was formulated to be the ratio of damaged feeder length to the total length of the feeders as a function of wind speed. They fitted a Gamma distribution to fit the outage duration patterns of the storms with the shape parameter being correlated with the square of 5-s gust wind speed. While their analysis sheds light on the behavior of power delivery systems stressed by storms, it cannot be used to predict those behaviors prior to an approaching storm.

Davidson et al. (2003) investigated the performance of the electric power distribution system in North and South Carolina using data from five hurricanes. They did an exploratory study to examine outage durations. Through a correlation-based study, they established that there is a weak relationship between the percentage of long-duration outages and increasing hurricane intensity. Based on overlaying the maps of outage durations and maximum gust wind speed, rainfall, and population density, they observed that the cluster of outages was more substantial for the densely populated areas. They also reported that the maximum gust wind speed and rainfall amounts did not seem to be related to duration of outages. Their study is exploratory in nature and although it is helpful for identifying the variables correlated with outage durations, it cannot be used in a predictive setting to get estimates of outage duration prior to a storm.

Nateghi et al. (2013) compared predictive accuracy of five distinct statistical methods for predicting the duration of power outages caused by hurricanes. They used an extensive dataset, including detailed information about the specifics of the power system and the geographic characteristics of the utility's service area in their study. They trained, tested, and validated the models they developed based on the methods of AFT regression, CPH regression, classification and regression trees (CART), multivariate adaptive regression splines (MARS), and Bayesian additive regression trees (BART). Through random holdout validation tests, they concluded that the BART-based forecast model offers the most accurate estimates of power outage durations, with mean errors substantially below those of the other models.

While the existing models in the literature are helpful in understanding the impacts of disasters on the reliability of power systems, they do not offer as strong of predictive accuracy as maybe desired for efficient storm preparation and restoration management. In this paper, we develop a predictive model, using the method of random forests to forecast duration of power outages prior to hurricane landfalls with reasonable accuracy. We then perform sensitivity analysis to gain insight into the key factors that are most associated with long power outage durations. Section 3 introduces the input data and the statistical method used to develop our models. Section 4 summarizes the results from our models. We then conclude our analysis by examining variable influence in Sect. 5 to identify the most important variables and the extent of their impact on explaining the variance of outage duration times. The conclusion of our study is presented in Sect. 6.

3 Data and methods

3.1 Data used

Many factors have been found to impact the vulnerability of power systems during hurricanes. These factors include, but are not limited to the number of customers served by the utility company in each area, the component inventories of the power system such as the number of poles, switches, and transformers, the geographic, topographic, and climatic characteristic of the area where the power system is located, and the characteristics of the hurricanes such as their wind speed and the duration of the time for which their wind speed is above the design threshold of the utility poles (Quiring et al. 2011).

Our data were provided by a utility company that serves the central Gulf Coast region of the USA. The service area consists of 6,681 grid cells with dimension of 12,000 feet by 8,000 feet (3.66 km by 2.44 km). The variables used in the initial stage of our model development are the same variables as used in Nateghi et al. (2013), a summary of which will be presented below. We used estimates of the maximum 3-s gust wind speed, and duration of time for which the wind speed exceeded 44.7 miles/h (20 m/s) for each grid cell provided by Impact Weather, a commercial forecasting service. Different types of land cover were also included in our analysis based on data from the National Land Cover Database (NLCD) 2001. As in Nateghi et al. (2013), the data pertaining to each type of land cover were provided at a resolution of 1 arc second, and the 21 land cover types were aggregated into the following eight classes: (1) water, (2) developed (including residential, commercial, and industrial), (3) barren, (4) forest, (5) scrub, (6) grass, (7) pasture, and (8) wetland. Soil moisture levels, antecedent precipitation, and mean annual precipitation were also incorporated into our model using the same data as in Nateghi et al. (2013). These variables were included to account for both short-term and long-term effects of climate on trees near power lines and on the stability of utility poles.

The power system characteristics that were included in our model were the number of poles, transformers, and switches, the length of overhead and underground lines in each grid cell, and the number of customers impacted by the hurricane. Our dataset consisted of 14,320 distinct power outages: each with a recorded duration (in minutes) spread over 6,681 grid cells. It is important to note that the available number of crews is a very important factor in predicting the duration of power outages. However, that data were not available to us and hence not incorporated into our models. We will return to this point in the discussion section.

In our analysis, a power outage is defined as the activation of a protective device causing a non-transitory loss of power associated with damage that needs to be repaired. Therefore, by this definition, the outage duration data included in our study do not include short duration interruptions that were automatically corrected by protective devices in the system. This definition also implies that a single power outage could affect varying numbers of customers.

3.2 Random forest

The method of random forest (RF) was developed by Breiman (2001). A random forest is a flexible, nonparametric data mining method that can capture the nonlinear structure of our dataset very well. It generally offers strong predictive accuracy and is reasonably robust to outliers and noise (Breiman 2001; Hastie et al. 2011). Moreover, because it is a non-parametric method and does not assume a particular distribution for the predictor and the errors, it is suitable for spatial data and does not suffer from the modifiable areal unit problem (MAUP). Yule and Kendall (1950) were the first to introduce the concept of MAUP, recognizing that spatial data are typically both auto-correlated and aggregated by spaces of varied dimensions (modifiable aerial units). The distribution of the response variable could therefore be significantly different depending on the scale or shape of the chosen grid cell in the analysis. These issues are typically not addressed in statistical modeling of spatial data (Thomas 1996).

The algorithm for developing a random forest in a regression setting is as follows:

1. Create a training set by selecting N bootstrap re-samples of the data. Treat the remaining data as the validation set to estimate the tree's prediction error.
2. Fit a regression tree to the training dataset by randomly selecting predefined m ($\ll M$) variables to split on; with M representing the total number of covariates that are used in the model.
3. Choose the optimal splitting values using the m allowable splitting variables, growing the tree to completion.
4. Test the predictive error with the remaining data.
5. Repeat the steps from (1) to (4) a predefined (K) number of times to develop K trees. In our analysis, we picked K to be 500, which has been shown to be the optimal number of trees for many datasets (Hastie et al. 2011). Final predictions are given by the un-weighted average of the predictions of the K regression trees.

In short, the random forest methodology involves fitting a series of regression trees to the dataset. Regression trees are low bias–high variance techniques, meaning that they can capture the general structure of the dataset very well (low in bias), but are highly sensitive to noise and outliers (high variance) (Hastie et al. 2011). Since the regression trees are fitted to randomly selected subsets of the input data, and the split values of the trees are also selected randomly, the generated trees are assumed to be independently identically distributed with negligible correlations among them. Averaging the final estimates of the regression trees will therefore lead to variance reduction. This low bias–low variance technique, therefore, yields improved accuracy while being robust to noise and outliers and is ideal for complex datasets.

Another advantage of this method is that, based on our experience, it is computationally faster than most other methods such as bagging, boosting, and BART. The computational efficiency of this method is particularly advantageous for utility companies that wish to run their models fast in the event of an approaching storm or hurricane.

In estimating the influence of the different covariates on outage durations, we used partial dependence plots. Partial dependence plots give an estimate of the relationship between a single predictor and the response variable, while other variables are held constant (Hastie et al. 2011). They are computed according to (1)

$$f_S(X_S) = \frac{1}{N}\sum_{i=1}^{N} f(X_S, x_{iC}) \tag{1}$$

where f_s denotes the response variable, X_s is the covariate for which the partial dependence plot is being estimated, and x_{ic} are the rest of the covariates in the training dataset other than X_s. The plots show the effect of X_s on f_s, while the influences of x_{ic} on f_s are accounted for.

4 Results

The outage duration forecast models were developed using the method of random forests incorporating the covariates introduced in Sect. 3.1 to estimate power outage durations caused by Hurricane Ivan (2004) in a central Gulf Coast state. The average outage duration in this service area was 2,870 min (approximately 48 h), and its standard deviation was 2,396 min (approximately 40 h). In order to compare the predictive accuracy of the random forest with previous models, we conducted 50 random holdout validation tests. In each of 50 independent iterations, we randomly held out 10 % of the data, where each outage record is a data point, as a validation set, leaving the remaining 90 % as the fitting dataset. The model was developed on the training set of data, and the predictions were tested against the validation set. The root-mean-squared error (RMSE) and the mean absolute error (MAE) values were used to measure the difference between the observed outage durations due to Hurricane Ivan and the predicted values using the random forest-based forecast model, averaged over the 50 repeated validation tests. Table 1 summarizes the out-of-sample predictive accuracy of our model and compares it to those from the BART model of Nateghi et al. (2013), and also to the case of using the mean outage duration as the predictor (i.e., no statistical model). Comparing the out-of-sample error to the 'mean-only' model will help understand what percentage of the variance in response is explained through the developed model.

It can be seen from Table 1 that our random forest model yields substantially lower prediction errors when compared to the estimates of BART. Its prediction error is also much lower the 'mean-only' model, which is an indication of the extent of the variance of the response explained through our model over using the mean of outages instead of having a statistical model. Table 1 shows that using the method of random forest leads to an 87 % improvement over using BART and 97 % improvement over not using a statistical model and using the mean outages as a predictor. It is important to note that the BART model of Nateghi et al. (2013) outperformed all other models of hurricane-induced power outages tested by Nateghi et al. (2013), including those developed by earlier papers focused on predicting hurricane power outage durations, yet our model offers substantially improved prediction accuracy. While the random forest model offers substantially better predictive accuracy, both this model and the BART model are specific to this utility's service area because they use privately known data about the design of the power system. We address this in the next section by developing models applicable outside of the service area of this particular utility.

Table 1 Comparison of the prediction results (in minutes)

Model	MAE	SD	RMSE	SD
Random forest	61.1	4.6	205.5	15.8
BART	471.7	18.4	894.0	45.4
"Mean-only" model	1,896.8	–	2,395.6	–

5 Identification of most influential variables

The objective of this section is to identify the most important variables in explaining the variability of outage durations and to develop simpler models based on a subset of the explanatory variables. These simpler models then can form the basis for generalizing this model to other geographic areas (e.g., different utility service areas), provided that the location-specific variables can be eliminated without significantly reducing model predictive accuracy. We then analyzed the degree of the influence of the most important variable on outage duration times.

5.1 Input variable classifications

We began by classifying the set of input variables into two distinct groups (see Fig. 1), those that can effectively be predicted prior to the occurrence of a storm and those than cannot be. The only input variable used in the model that cannot be accurately estimated prior to an impending storm is reported outage causes that are recorded by repair crews at the time of repair. Predictable variables were further subdivided into static and dynamic variables. The dynamic variables could potentially vary over a given hurricane, but the static variables are fixed over that time period.

The dynamic predictable variables include the following: (1) hurricane characteristics such as wind speed and wind duration above 44.7 miles/h (20 m/s), both of which can be predicted prior to the event, (2) dynamic characteristics of the power system such as the type of protective device that was activated to isolate the damage during the event, and (3) the geographic area's climate information such as fractional soil moisture levels at different depths.

Static predictable variables include both characteristics specific to the power system such as the number of poles, switches, transformers, and miles of power lines, and the geographic characteristics of the area in which the power system is located, such as the land slope, elevation, and the types of land cover. Note that some of these variables do change slowly over multiple years, but for the purpose of hurricanes occurring in a given hurricane season, they are effectively static within that season. Our final analysis will help identify the degree of the sensitivity of the prediction models to each of these classes of variables.

5.2 Partial dependence plots

We first developed our model, using the method of random forest, by including all the covariates introduced in Sect. 3.1. Partial dependencies were then plotted to identify the marginal influence of the particular covariate on the response variable, controlling for all the other variables. Many of the partial dependence plots showed nearly straight, horizontal

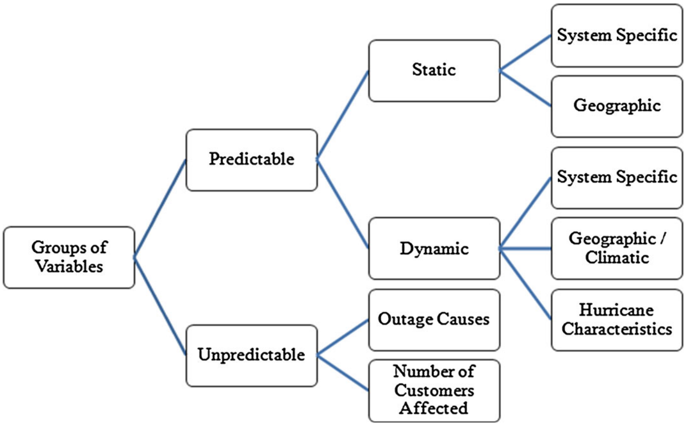

Fig. 1 Classification of input variables

lines, indicating that a large number of the covariates provide very little help with explaining the variations in outage duration times. All the covariates whose partial dependence plots had near-zero slopes (through visual inspection) were removed. We then developed a simpler model using only a subset of the original covariates whose partial plots had nonzero slopes without losing much predictive power as described below.

The subset of the variables incorporated into the simpler model include the following: (1) topographic data such as the elevation and the slope of the land, compound topographic index (which is a measure of relative wetness of a particular grid cell), the type of land cover, and mean annual precipitation (MAP) (predictable–static–geographic variables), (2) the hurricane's wind speed and duration of winds above 44.7 miles/h (predictable dynamic variables), and (3) Standardized Precipitation Index (SPI), and fractional soil moisture levels 1 day prior to the hurricane landfall at the following depths: 0–10 cm ($SM_{0–10}$), 10–40 cm ($SM_{10–40}$), and 40 cm to bedrock ($SM_{40\text{-Bedrock}}$) (predictable–climatic–geographic–dynamic variable). Our reduced model did not include the unpredictable variables or variables specific to a particular utility system (e.g., miles of line in each grid cell). Our partial dependence plots indicated that wind speed and the duration of winds above 44.7 miles/h are the most critical factors in determining the restoration times. This finding implies that longer duration outages occur at higher wind speeds, and therefore, it would take longer for the repair crew to restore the system for more severe storms. It should, however, be noted that approximately 99 % of the line miles in our study are aboveground, and the sensitivity of the system to wind speed and duration could potentially be different for a system that has more line installed underground.

The antecedent precipitation and the geographic characteristics of the area also have a considerable impact on the response variations. Standardized Precipitation Index (SPI) is expected to have an impact on outage restoration times because weather patterns—prior to hurricane landfall—that are either substantially drier or wetter than the long-term average in the area may stress vegetation, making it more likely to fail. The geographic characteristics of the land (such as elevation and aspect) and soil moisture are thought to impact the restoration time because they directly influence how easy or hard the repair crew's access to the damaged areas will be. For instance, utility personnel for this area report that wetter soils will cause the crew trucks to get stuck in the mud, causing delays in crew

Table 2 Prediction results of the full model and simpler models for Hurricane Ivan with mean of 2,870 and standard deviation of 2,396 min

Models	MAE	RMSE
Random forest (all variables)	60.8	205.5
Random forest (subset of variables)	65.1	218.9

Table 3 Prediction results of the full model and simpler models for Hurricane Dennis with mean of 1,010 min and standard deviation of 800 min

Models	MAE	RMSE
Random forest (all variables)	54.9	116.5
Random forest (subset of variables)	56.1	117.7

Table 4 Prediction results of the full model and simpler models for Hurricane Katrina with mean of 2,076 min and standard deviation of 2,222 min

Models	MAE	RMSE
Random forest (all variables)	62.6	194.7
Random forest (subset of variables)	66.3	207.4

Table 5 The p values associated with the two-tailed Student's t test between the full model and reduced model for each hurricane

Hurricane	p value (MAE)	p value (RMSE)
Ivan	1.054e−05	2.574e−05
Katrina	4.644e−10	<2.2e−16
Dennis	0.2096	0.8686

access to damaged areas. Moreover, soil moisture levels are thought to impact the stability of poles and how easily the trees will be uprooted during high-wind events.

Table 2 below shows the MAE and RMSE for a holdout comparison of the two models for Hurricane Ivan, namely, the full model and the reduced model. It can be seen that the values of the errors for 50 random holdout validations are not substantially different, indicating that the simpler model does not come at the cost of a substantial loss of predictive power.

We then repeated this modeling process for two additional hurricanes, Hurricane Dennis and Hurricane Katrina. We repeated the 50-fold cross-validation comparison independently for each hurricane (Tables 3, 4). The difference between the full models and reduced models for each of the hurricanes was compared based on a two-sided Student's t test with unequal means (Table 5). Even though the difference between the full and reduced predictive models for Hurricanes Ivan and Katrina is statistically significant with p values below 0.01, the difference between the predictive errors is small for practical purposes and the error values associated with the reduced model are still much lower than all of the other existing models in the literature. The improved simplicity from eliminating the unpredictable variables is a significant benefit, offsetting the relatively small, though statistically significant, loss in predictive accuracy.

As explained earlier in Sect. 3.2, partial dependence plots help understand the influence of the input variables on the response variable in nonparametric models. More specifically, they are a great way of representing the average marginal influence of changing one input covariate (the plotted covariate) while the effects of the rest of the inputs are held constant (Hastie et al. 2011; Friedman 2001). They have been widely used in the literature to visualize dependencies between the response variable and the independent variables used in random forest models (Cutler et al. 2007; De'Ath 2007; Nateghi 2012; Shortridge and Guikema 2014). The partial dependencies were plotted for the key variables included in the reduced-complexity forecast model (as explained in Sect. 5.2). The partial dependence

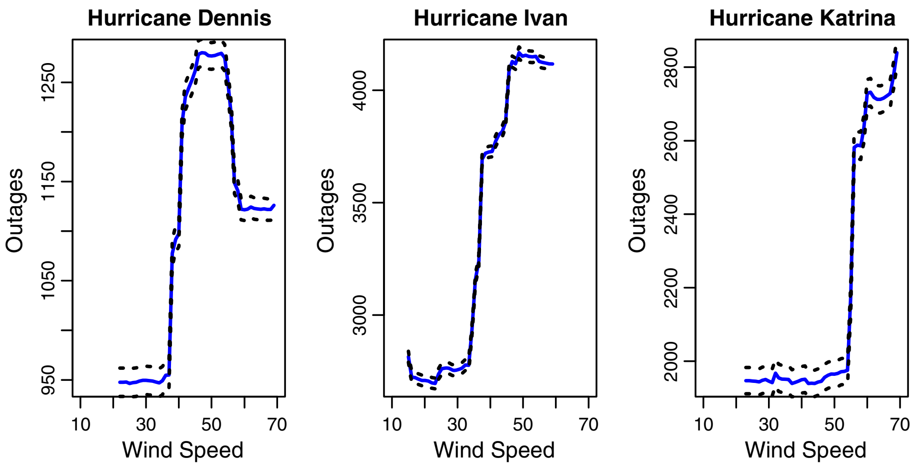

Fig. 2 Partial plots of wind speed for Hurricane Ivan, Katrina, and Dennis

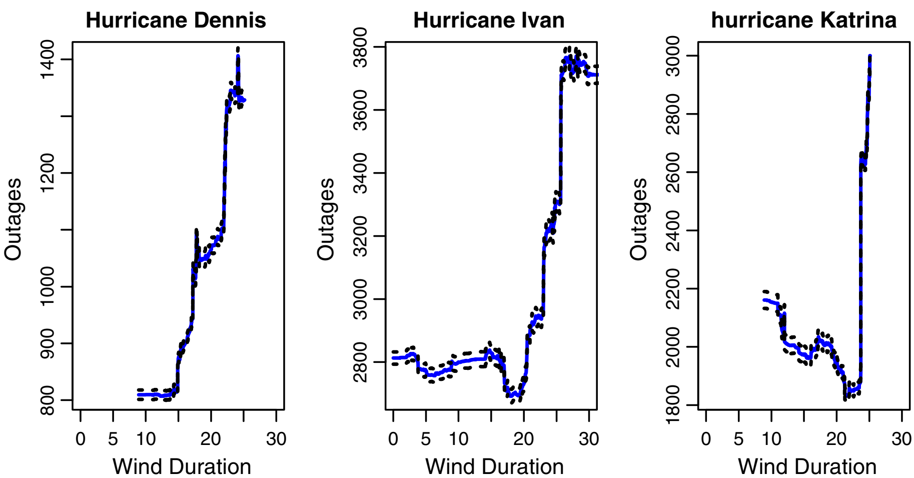

Fig. 3 Partial plots of wind duration for Hurricane Ivan, Katrina, and Dennis

plots of the key variables are shown below (Figs. 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15). Please note that the axes ranges are not always the same across all hurricanes. The ranges on the plots have been selected such that the dependencies are depicted most clearly. For each plot, the degree by which a covariate influences the outage duration time is the range of the marginal influence of that variable on the response variable; the difference between the maximum predicted Y, the response variable, and the minimum predicted Y over the range of the response variable. Examination of the slopes of the plots (Figs. 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15) shows that hurricane characteristics (i.e., wind speed and wind duration) are the most important predictive covariates across all the hurricanes, followed by the climatic variables (e.g., mean annual precipitation) and geographic variables (e.g., land cover types). Moreover, power outage durations for Hurricane

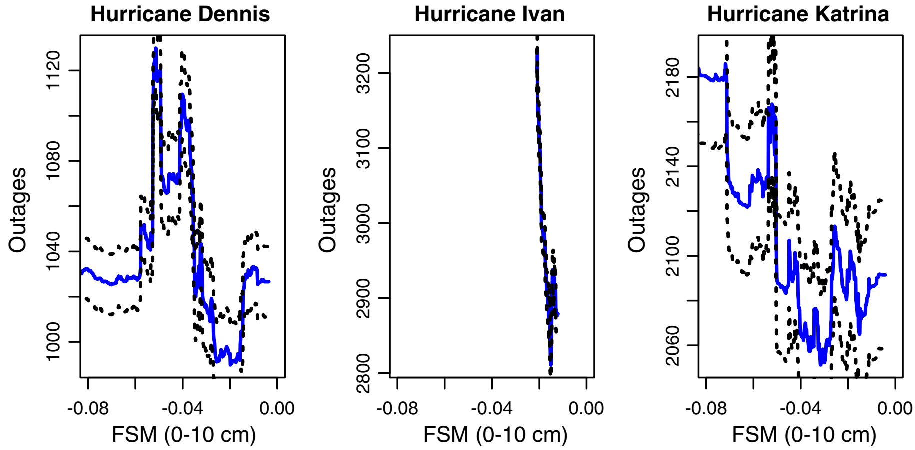

Fig. 4 Partial plots of fractional soil moisture 1 day prior to hurricane landfall at the depth of 0–10 cm for Hurricane Ivan, Katrina, and Dennis

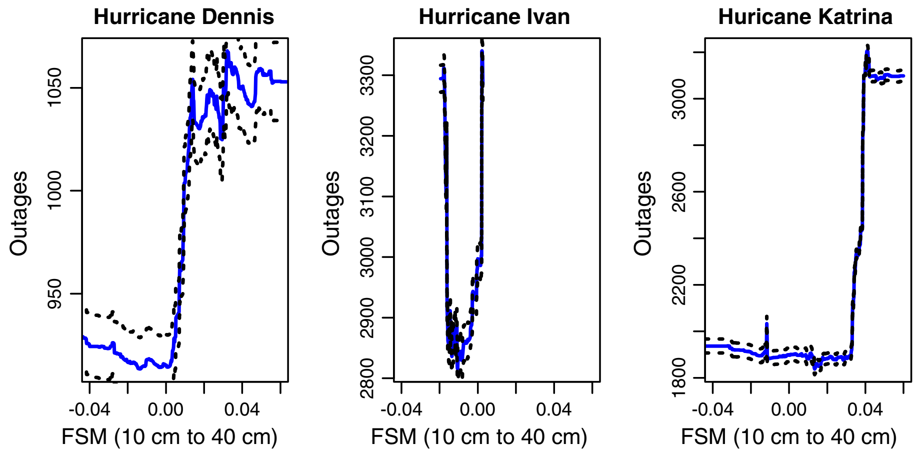

Fig. 5 Partial plots of fractional soil moisture 1 day prior to hurricane landfall at the depth of 10–40 cm for Hurricane Ivan, Katrina, and Dennis

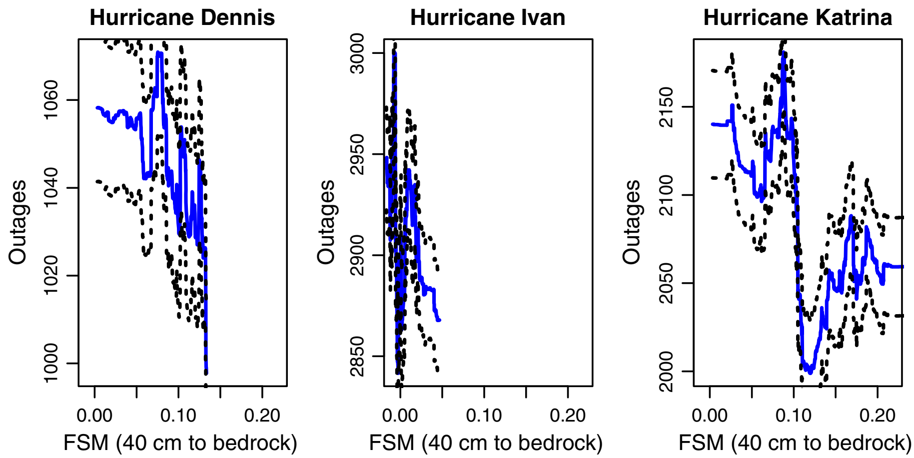

Fig. 6 Partial plots of fractional soil moisture 1 day prior to hurricane landfall at the depth of 40 cm to bedrock for Hurricane Ivan, Katrina, and Dennis

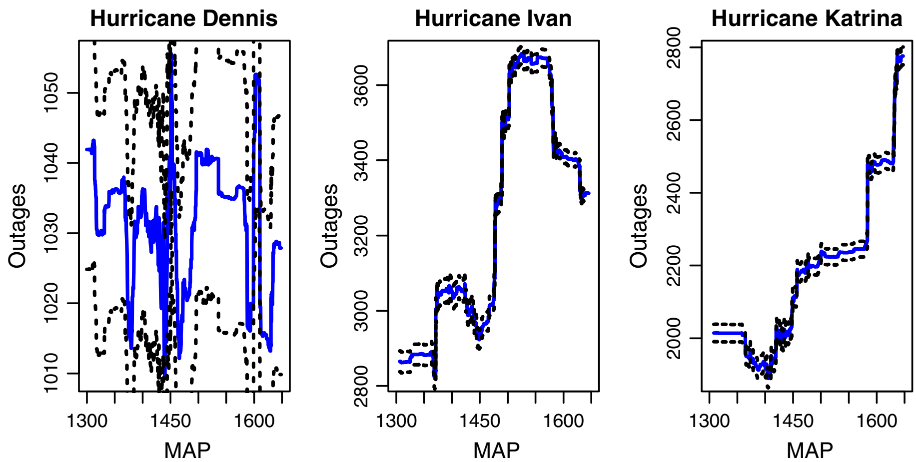

Fig. 7 Partial plots on mean annual precipitation (MAP) for Hurricane Ivan, Katrina, and Dennis

Dennis are less sensitive to wind speed and duration than for the other two hurricanes (Figs. 2, 3). The utility providing the data reported that relative to the other two hurricanes, they had more crews available per outage for Hurricane Dennis. It can be hypothesized that the reduced sensitivity to the input variables for Hurricane Dennis is an indication of this high level of crew preparedness after Hurricane Dennis, leading to the prediction model being less sensitive to our input covariates and possibly more sensitive to the number of crews dispatched.

As mentioned earlier in Sect. 3.1, the number of restoration crews was not included in this analysis since that data were not available to us. This is a significant limitation in terms of generalizability of this work. The results of our analysis are valid as long as the utility company selects its crew levels consistently prior to each event. We believe that adding the

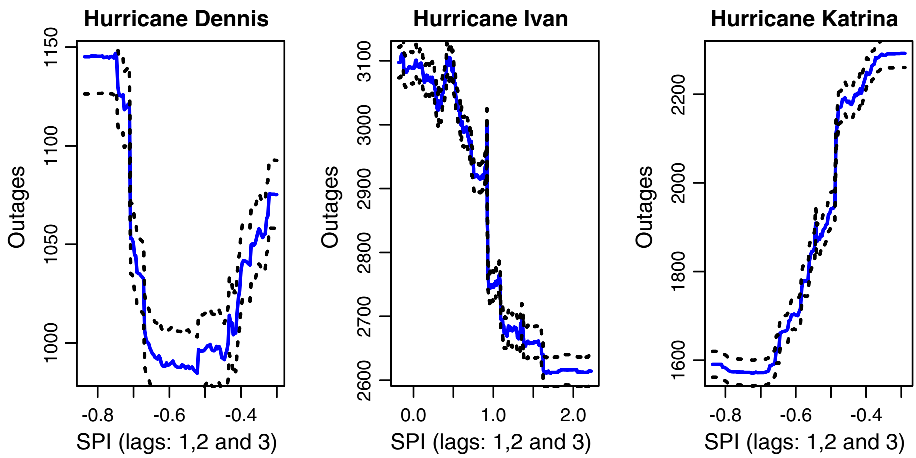

Fig. 8 Partial plots of SPIs calculated with lags of 1, 2, and 3 months for each of the tree Hurricanes of Ivan, Katrina, and Dennis. SPI with lags of 1, 2, and 3 months were averaged, and the average was used as a single covariate in the model

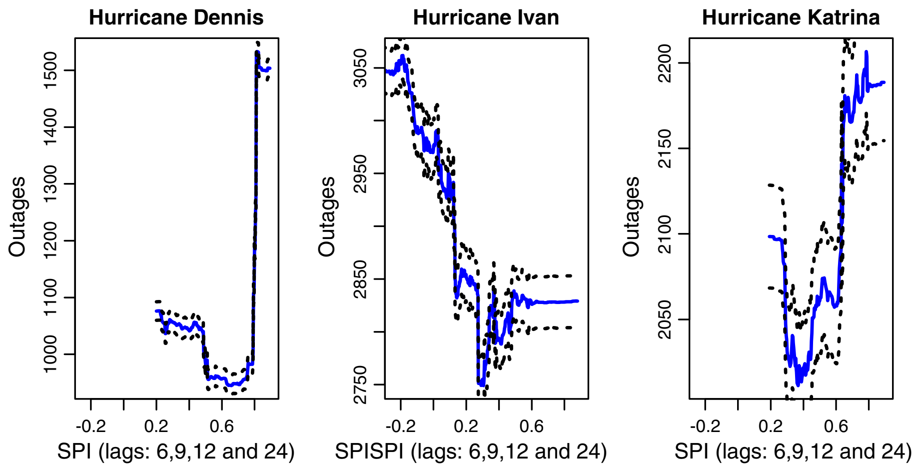

Fig. 9 Partial plots on SPI calculated with lags of 6, 9, 12, and 24 months for each of the tree Hurricanes of Ivan, Katrina, and Dennis. SPI with lags of 6, 9, 12, and 24 months were averaged, and the average was used as a single covariate in the model

number of crews available for restoration could significantly improve the accuracy of the model.

6 Conclusion

Electric power outages caused by hurricanes result in substantial losses to society. Prolonged power outages can adversely impact other infrastructure systems, leading to severe societal and economical costs. Traditionally, utilities make restoration plans based on

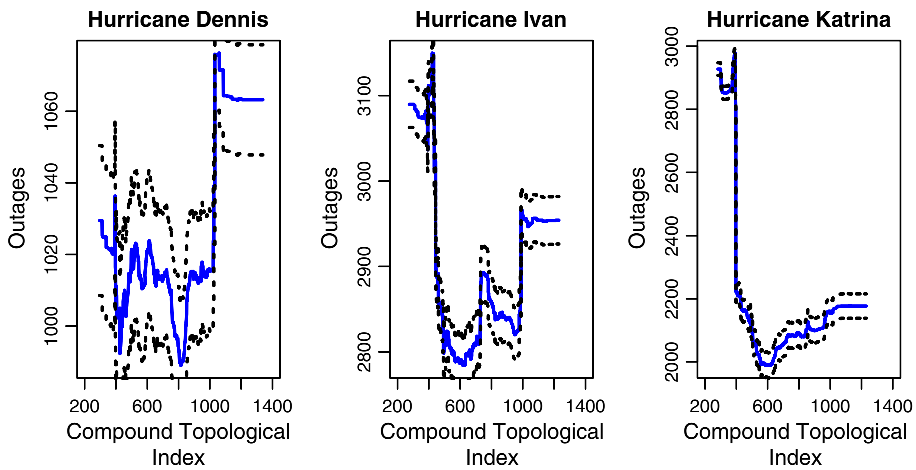

Fig. 10 Partial plots on mean values of Compound Topological Index (CTI) for each of the tree Hurricanes of Ivan, Katrina, and Dennis

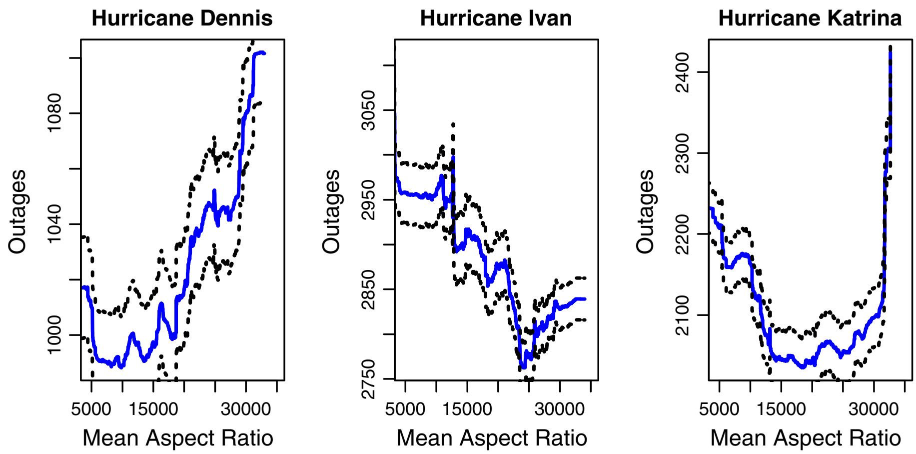

Fig. 11 Partial plots on mean values of aspect ratio for Hurricanes Ivan, Katrina, and Dennis

managerial judgment and past experience, and this may lead to inefficient use of resources and over- or under-preparation, if the experience-based estimates are not accurate. Having accurate estimates of power outage duration is also very important for better informing customers and other utilities, allowing them to make more efficient restoration plans. Accurate hurricane damage forecasts can also be used as inputs to risk-informed investment decision frameworks to mitigate the impact of disasters on infrastructure systems (Lambert et al. 2013; Joshi and Lambert 2011).

In this paper, we show that the duration of power outages caused by hurricanes can be accurately predicted prior to landfall based only on information that can be estimated before landfall. The results indicate that our random forests-based forecast model can predict outage restoration times with an improved accuracy over the existing models. It is

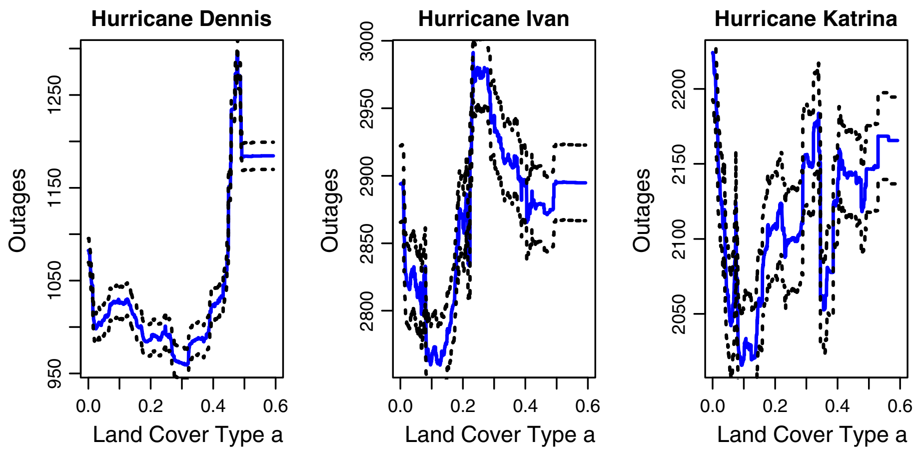

Fig. 12 Partial plots on medium-intensity developed land cover type (e.g., apartment complexes, commercial or industrial complexes) for Hurricanes Ivan, Katrina, and Dennis

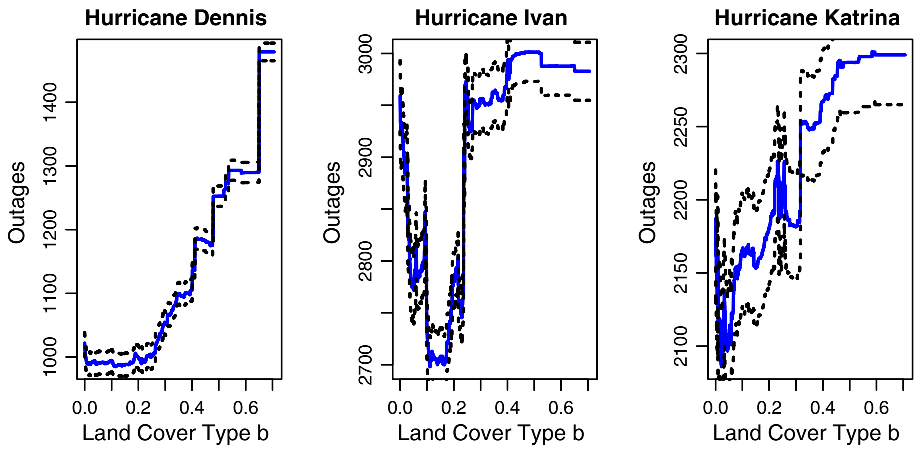

Fig. 13 Partial plots of low-intensity developed land cover type (e.g., single-family housing units) for Hurricanes Ivan, Katrina, and Dennis

87 % more accurate than the BART model used by Nateghi et al. (2013). Our model yields higher predictive accuracy compared to the existing models in the literature and also yields insights into the most important factors driving the outage duration prediction models through the use of partial dependence plots. Our models show that the most critical variables are the wind characteristics of the storms and the climatic and geographic characteristics of the service area such as the mean annual precipitation, soil moisture levels, and Standardized Precipitation Index, a measure of local deviations from long-term precipitation. Having accurate estimates of the characteristics of the hurricanes such as wind speed and duration of gust wind speed and also accurate measurements of the climatic and geographic variables such as mean annual precipitation, soil moisture, and Standard Precipitation Index values prior to the hurricane can enable accurate prediction of post-storm restoration times.

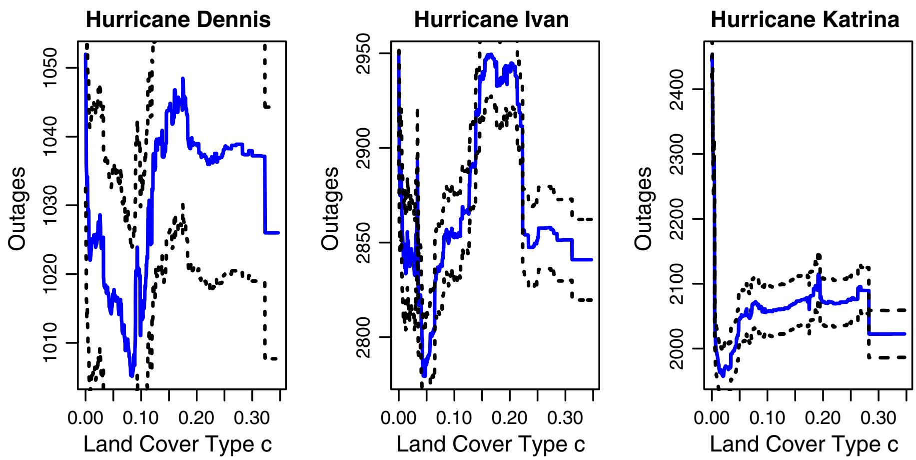

Fig. 14 Partial plots on developed open space land cover type (e.g., parks and golf courses) for Hurricanes Ivan, Katrina, and Dennis

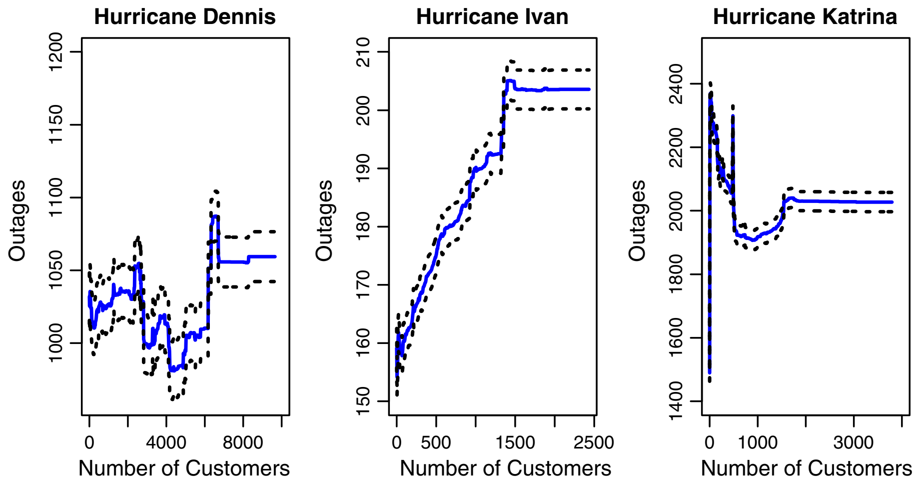

Fig. 15 Partial plots on developed the number of customers for each of the tree Hurricanes of Ivan, Katrina, and Dennis

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