GEOSPATIAL MODELING OF ROADSIDE VEGETATION RISK ON DISTRIBUTION POWER LINES IN CONNECTICUT

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ABSTRACT:

Roadside trees cause almost 90% of the power outages in the forested Northeastern US. Management of roadside vegetation risk on electrical infrastructure demands timely and accurate information on forest conditions. Tasking conventional ground-based scouting methods along thousands of kilometers of power lines in a repeated fashion are labor-/cost-/time-intense. Geospatial and earth observation (EO) technologies serve as cost-effective tools in monitoring, inspecting, and managing utility corridors. EO technologies, from drones, aircraft, to satellites can efficiently acquire information over large areas at regular intervals while probing forest physical structure and health conditions. LiDAR is a useful data stream for modeling terrain conditions and estimation of multiple forest inventory variables that explain the physical structure of the forest. Various EO imagery provides information on bio-physical characteristics of trees that affect forest health at finer granularity. The goal of this study is to combine multiple environmental variables to develop a spatially-explicit vegetation risk model using machine learning algorithms. Some of the key inputs used in our analysis include LiDAR-derived tree-related variables (e.g., tree height, proximity pixels, canopy cover), LiDAR-derived terrain data (slope, aspect, topographic index), soil characteristics, vegetation management data (tree trimming methods), infrastructure data (wire type), and power outages reported from 2005 to 2017 in Connecticut. Findings of this research will be vital in informing vegetation management decision-making processes, which eventually reduce power outages and the cost of utility corridor maintenance.

1. INTRODUCTION

Electricity is an essential basic need of modern life (EIA, 2021). Power interruptions cause many compromises in transport, healthcare, communication, national and economical security (NIAC, 2018). Power failures are caused by many factors, such as weather, vegetation patterns, and utility practices (Lindstrom and Hoff, 2020). Most of the tree failures that cause power outages are weather related (Campbell, 2012) and cause non-defective trees to fall on power lines (Finch and Allen, 2001). Kenward and Raja (2014) reported that more than 80% of outages are caused during weather events. The Congressional Research Service (CRS) Report for Congress (Campbell, 2012) states that high winds with precipitation from seasonal storms cause massive disruptions to the electric grid. Hines and others (2009) analyzed the events causing outages from 1984 to 2006 using data available from North American Electric Reliability council (NERC) and showed that almost 44% of the events are weather related. In late August 2011, Hurricane Irene caused power loss for more than 6.5 million customers across 14 states in the US. According to electric utilities in the Northeastern US, roadside trees cause up to 90% of outages during storms (Eversource, 2019). Tropical storms, such as Isaias, Sandy and Irene resulted in massive damage in this region which eventually led to prolonged outages and more than one million customers were affected. Winter storm Alfred and hurricane Irene in 2011 which affected 1.2 million customers, caused extensive damage in the northeastern U.S and the complete restoration of power outages took 9 to 12 days (McGee et al., 2012). In 2012 over 225,000 power outages were caused following hurricane Sandy in Connecticut. Hurricane Isaias caused power outages for more than 2 million customers across states in the Northeast in August 2020. In the same month, Hurricane Laura caused power outages for nearly 400,000 customers (Climate central, 2020). When focusing on Connecticut only, Isaias caused massive destruction to the power grid in Connecticut. Nearly 675,000 customers lost power and over 21,000 damage locations were reported throughout the state.

Electric utilities make substantial financial investments annually on roadside vegetation management programs to ensure reliable electrical services and to improve the resiliency of the power grid in extreme weather events. According to PURA (2013), vegetation management is the removal of trees, shrubs, and other vegetation that pose a risk to the utility infrastructure and the retention of trees and shrubs that are compatible with utility infrastructure. In Connecticut, vegetation management is restricted within the utility protection zone (UPZ), which is within 2.5 lateral meters of the power lines from ground to sky (PURA, 2013). The monetary cost associated with tree trimming is considered as the largest cost factor of the total money spent on power distribution system maintenance (Radner et al., 2002 and Lovlace et al., 1996). Utility companies manage tens of thousands of kilometers of power lines, and their biggest challenge is to determine when and where vegetation may become a risk to power lines. Accurate identification of vegetation risk areas and ideal use of vegetation management interventions alongside other grid hardening programs are crucial for maximizing grid resilience and reliability. Data-driven vegetation management decision making demands spatially explicit and temporally conversant information on roadside forest conditions. Conventional vegetation scouting/inspection methods along utility corridors are labor-/time-intense and cost prohibitive.

Geospatial and earth observation (EO) technologies serve as cost-effective tools in monitoring, inspecting, and managing utility corridors. EO technologies, from drones, aircraft, to
satellites can efficiently acquire information over large areas at regular intervals while probing forest physical structure and health conditions. The Light Detection and Ranging (LiDAR) is known as one of the emerging remote sensing technologies which can be used in obtaining terrain models, estimation of multiple resource inventory variables through active sensing of three-dimensional (3D) forest vegetation (Reutebuch, 2005). Using LiDAR, numerous tree variables have been derived such as height and size of individual trees, canopy closure, volume, and biomass of forest stands (Andersen et al., 2005, Hinsley et al., 2006, Means et al., 2000, Naesset, 2002, Persson et al., 2002, Popescu and Zhao, 2007). Moreover, tree height in deciduous forests during leaf-off conditions (Parent and Volin, 2015), canopy rugosity (Parker and Russ, 2004), mapping stem locations and tree crowns (Holopainen et al., 2013), and stem diameter (Kankare et al., 2015; Tanhuanpaa et al., 2014) have been derived using this technology. On top of that, LiDAR can store and review or utilize forest data over time. This will allow LiDAR to monitor changes in tree height and crown radius over a five-year period (Duncanson and Dubayah, 2018).

Understanding what environmental factors contribute to tree failures is critical for developing spatially explicit vegetation risk models. Confounding factor analysis can primarily be performed at the circuit level, which is at coarser granularity, as well as at the device exposure zone (DEZ) level (the outage locations correspond to isolating devices each of which protect a section of power line called a device exposure zone). Most of the studies have been conducted at the circuit level (Taylor et al., 2022, Zhu et al., 2007). A DEZ level modeling approach will account, in addition to forests related factors, multitudes of other environmental factors, soil and terrain (soil, slope and aspect), utility infrastructure related variables (overhead length, overhead to underground powerline length), and vegetation management practices (e.g., tree trimming and hazard tree removal). From the perspectives of utility industry and as well as the regulatory bodies, the envisioned outcome would be to identify and localize where the “HOT” spots are for tree failures during storms. A finer granularity DEZ-level vegetation risk model is vital in informing vegetation management decision making processes. This will eventually reduce power outages and the cost of utility corridor maintenance. The goal of this study is to combine multiple environmental variables to develop a spatially-explicit vegetation risk model using machine learning algorithms. Also, we are interested in finding the major environmental variables that contribute to tree failures along the power lines.

2. METHODS

2.1 Study Area

We conducted our analysis in the state of Connecticut. Eversource Energy, the main utility company in the state, manages nearly 27,000 km of distribution lines (Figure 1). Eversource delivers electricity to almost every town in Connecticut, serving~1.2 million customers (Eversource, 2021). The topography is generally hilly with elevation ranging from sea level in the south to nearly 750 m in the northwest. All the variables and data are derived/reported at the DEZ level. The location of an outage is reported at the associated DEZ isolating device regardless of where the actual cause (tree failure) of the outage occurred within the DEZ. The distribution powerline data set contains approximately 49,000 DEZs within 900 circuits. The length of DEZs range from 100s to 1000s of meters.

2.2 Data

2.2.1 LiDAR-derived tree heights: We used publicly-available LiDAR data that was acquired in early spring 2016 during leaf-off condition, (point density 2.2 pts/m²) to derive canopy height model (CHM) and successive vegetation parameters along the power lines (Parent and Volin, 2015).

Previous literature has shown that minimum of 4–8 pts/m² spatial resolution is required to map individual tree crowns (Evans et al., 2009 and Laes et al., 2008). Therefore, we used the concept of “Proximity tree pixels (pPix)” (Figure 2) explained by “Wanik et al., 2017” to create the LiDAR derived tree parameters described in Table 1. pPix refers to the 1 m pixels in a canopy height model (CHM) that are tall enough and close enough to contact a power line in the event of a whole or partial tree failure. Proximity pixels are identified from the CHM as pixels with a height larger than the distance from the pixel at ground-level of the tree to the point at the location of the nearest power line (Wanik et al., 2017).

2.2.2 Power outages, Utility infrastructure, and vegetation data: We obtained power outage data for the period of 2005-2017 from Eversource Energy. The outage database allowed us to identify the approximate locations of tree-related outages occurred during windstorms. Database includes comprehensive information for each outage (trouble spots) recorded in its
Regarding isolating device, such as date of occurrence, restored date and time, device exposure zone ID, circuit id, number of customers affected, affected pole id, cause of damage, actions taken to repair and geographic locations.

Figure 2. Proximity pixel modelling using LIDAR-based canopy height model (Proximity pixel if tree height > d)

Table 1. List of explanatory and response variables included in the machine learning model development

| Type            | Abbreviation | Description                                      | Source   | Variable Type |
|-----------------|--------------|--------------------------------------------------|----------|---------------|
| Vegetation      | medianH      | pPix of median height                            | LiDAR    | Continuous    |
|                 | pTreeCov     | Canopy Cover percentage                          | NLCD     | Continuous    |
|                 | h50_t        | Percentage of pPix with heights higher than 15m  | LiDAR    | Continuous    |
|                 | exp15_t      | Percentage of pPix that are 4.5m ft taller than surrounding 8m | LiDAR    | Continuous    |
|                 | Clsr_tot     | Percent canopy area around DEZ with tree height higher than 15m | LiDAR    | Continuous    |
|                 | wind_tot     | Percent of pPix on wetland soils                 | LiDAR    | Continuous    |
|                 | rcky_tot     | Percent of pPix on extremely rocky soils          | CT Deep  | Continuous    |
|                 | shlw_tot     | Percent of pPix on shallow soils (<40cm to bedrock) | CT Deep  | Continuous    |
|                 | stp_tot      | Percent of pPix on steep slopes (>50pct) and with aspect toward DEZ point | LiDAR    | Continuous    |
|                 | avgGrndAz    | Average ground azimuth                            | NLCD     | Continuous    |
|                 | gSlp_mean    | Percent of pPix on ground slope (<50pct) and with aspect toward DEZ point | NLCD     | Continuous    |
|                 | TPI150_mm    | TPI (z-medainZ) for window approx. 150m in radius, to determine landform | NLCD     | Continuous    |
|                 | TPI450_mm    | TPI (z-meanZ) for window approx. 450m in radius, to determine landform | NLCD     | Continuous    |
| Infrastructure  | coverWire    | Overhead lines are covered or not                | Eversource| Binary        |
|                 | UG_ratio     | Ratio between overhead and underground power lines | Eversource| Continuous    |
|                 | length_km    | Primary OH Length                                 | Eversource| Continuous    |
| Class           | petETT       | Presence of outages (Yes/No)                     | Eversource| Binary        |
| Vegetation      | SUM_ETTLen   | Total Enhanced tree trimming length in the DEZ    | Eversource| Continuous    |

For the modeling, we only included outages, which were caused by trees either as broken stem or windthrow (i.e., Entire tree uproots). Outages were only included if they were tree-related and associated with a primary isolating device, and occurred during weather conditions: blizzard, hurricane, ice storm, rain, snow, thunderstorm, tornado, and high winds. The outage data includes nearly 53,000 tree-related incidents for the time period of interest. All utility infrastructure geospatial layers were acquired from Eversource Energy. The DEZs are represented as polyline geometry, which includes attributes of; conductor segment length, associated isolating device information, major

wire type of the conductor (e.g.; aerial cable, large bare wire, large-covered wire, large spacer cable, etc.) and length of underground powerline. We also obtained geospatial layers corresponding to Enhance Tree Trimming (ETT) from Eversource Energy. ETT refers to the removal of above and below that are 8 feet (2.4m) to the side of the power lines and removal of dead, dying, or diseased trees (Eversource, 2019). The data layer consists of several information such as date of trimming year, work type, and object id.

2.2.3 Secondary products: We used previously described LiDAR and NLCD (2016) data to develop different potential indicators (as shown in Table 1), such as the percent of proximity pixels (pPix) on steep slopes and percent of pPix with percent canopy cover and topographic indexes. Also, the percentage of pPix on different soils (such as wetland soils, rocky soils, and shallow soils) were calculated using the USDA Natural Resources Conservation Service (NRCS) soil data.

2.3 Correlation Analysis

We used Spearman’s rank test to determine the relationship between each explanatory variable and response variable (Equation 1). The Spearman’s rank correlation coefficient is generally denoted as \( \rho \) for a population parameter and as \( r_s \) for a sample statistic. This method is more appropriate for a dataset with skewed or ordinal data and is robust when extreme values are present. (Mukaka, 2012)
where, true-positives (TP) are the number of outcomes where the model correctly predicts the positive class, true-negatives (TN) are the outcomes where the model correctly predicts the negative class, false-positives (FP) are the outcomes where the model incorrectly predicts the positive class, and false negatives (FN) are the outcomes where the model incorrectly predicts the negative classes.

2.6 Evaluation of variable importance

Shapley Additive exPlanations (SHAP) proposed by Lundberg and Lee (2017) was used to evaluate the importance of each predictor variable. The SHAP method is based on the game theoretic approach (Shapley, 1961; Lundberg et al., 2018) and allocates payouts (i.e., importance) among all pairs of features, not only limited to the individual features. This helps to explain the modelling of the local interaction effects (Li et al., 2020b). Partial dependence plots (PDP) (Goldstein et al., 2015) were generated to visualize the average relationship between the response variable and highest contributed important variables.

3. Results

3.1 Correlation Analysis

Spearman’s correlation among 18 continuous explanatory variables is shown in Figure 3. Tree pPix variables such as Percentage of pPix with heights higher than 15m (h50_t), Percentage of pPix that are 4.5 ft taller than surrounding (exp15_t), and Percent canopy area around DEZ with tree height higher than 9m (Clsr_tot) reported highest correlation between these three variables. Moreover, slightly higher correlation could be observed between percent of pPix on extremely rocky soils (rcky_tot) and total percent of rocky soils/wetland soils/shallow soils (badSoils). In contrast, other explanatory variables reported less correlation values (Figure 3).

3.2 Performance estimation

A confusion matrix for random forest classifier can be used to summarize and visualize the prediction values (Figure 4). It shows the true predicted and false predicted labels for each outcome class. Based on test results, the overall accuracy of our RF classifier is 72%. As seen in Figure 4, class 0 is predicted to be better than class 1. Moreover, FP and FN values have shown slightly higher values even though they are less than TP and TN values. The mean area under receiver operating characteristic curve (AUC-ROC) is shown in Figure 5. AUC-ROC score is found to be higher according to the RS classifier which is 0.78.
Most of the soil and terrain variables (e.g., Topographic index (z-medianZ) for window approx. 150/450m in radius, to determine landform, Average ground azimuth, Percent of pPix on shallow soils, and Percent of pPix on steep slopes (>50pct) and with aspect toward DEZ point) showed very little contribution to the overall model performance. The first eight explanatory variables have shown approximately 90% contribution to the model. Figure 7 shows the partial dependence plots, which elucidate how the predictions partially depend on the values of the input variables of interest. The explanatory variable of interest was plotted on the X axis and y axis shows the change in response variable. Primary OH Length, median height of pPix, Canopy Cover percentage, and total Enhanced tree trimming length in the DEZ contributed to increased predicted outages. The percentage of pPix with heights higher than 50 ft (15m) had a nonlinear pattern. Percent of pPix on extremely rocky soils, and percent of pPix on wetland soils showed slight impact on increasing predicted outages.
4. DISCUSSION

The purpose of this study was to develop a geospatial model that can localize the vegetation risk areas along the power lines and to identify confounding environmental variables contributing to tree failures. We used Random Forest (RF) classification algorithm for our analysis. Because RF has been widely used in outage prediction models (Nateghi, 2014 and Wanik et al., 2017) and previous studies have shown the applicability of Random Forest in outage prediction models (Li et al., 2021a). Parr and others (2019) have shown that presence of multicollinearity in the data provides the least meaningful importance values. Therefore, we attempted to find the correlated explanatory variables in the beginning of the analysis and kept one input variable from the highly correlated cluster. Bradley (1997) and Fawcett (2006) have shown the use of area under the receiver operating characteristic curve (AUC-ROC) to evaluate the model performance in machine learning. AUC-ROC can measure the ability of a classifier to distinguish between classes. According to the results of RF model, we can observe that FN and FP numbers show somewhat higher values even though their values do not exceed the TP and TN values. This can affect the accuracy of the overall model prediction. AUC-ROC curve showed plausible values. When AUC-ROC is between 0.5 and 1, there is a high chance that random forest classifier can distinguish the positive classes labels from negative class labels. According to the results of variable importance analysis, we can find that 90% of the model has been explained by 8 variables. Our results are in alignment with the previous studies, such as Wanik et al., (2017) who found utility infrastructure (total overhead length and sum of assets) and proximity pixel variables as highest importance variables. This implies the importance of including both tree related and utility infrastructure data to the outage prediction modeling process. A similar study conducted by Li et al., (2021a) found that geographical/terrain factors, such as altitude, slope, slope direction, and longitude greatly contributed to the accuracy of the prediction model. However, most soil and terrain variables showed the least significance to the overall model prediction in our study. A possible reason could be, we included power outages occurred due to both tree and limb/branches failures in our analysis. In the effect of tree limbs and branches failures, we can assume that soil and terrain variables have the least impact on determining outages. Another potential reason could be the spatial granularity of the soil data. Soil data layers are generally reported at much coarser resolution which could overlook the local variabilities. Our results elucidated the importance of vegetation management and grid hardening programs in outage prediction and provided motivation to keep investing in such measures to increase the grid reliability and resilience. Tree decay is one of the natural phenomena occurring in trees and 76% of the trunk failures involve a decay (Kane, 2008) and leads to loss in moment capacity of tree branches and stems (Ciftci et al., 2014). There is a higher probability of these unhealthy trees falling onto powerlines during the events of storm and normal weather conditions. Therefore, it is vital to include the tree's health condition as an input variable to the vegetation risk modelling process.

5. CONCLUSION

In this study, we investigated the prediction of power outages on distribution lines using multiple environmental variables in Connecticut. Our analysis was conducted at the device exposure zone level. Utility infrastructure data (Primary overhead length, overhead lines are covered or not), tree variables (Percentage of pPix with heights higher than 15m, canopy cover percentage, median height of proximity pixels) and vegetation management variables (total enhanced tree trimming length in each DEZ) were found to be highly important predictor variables.

Figure 7. The partial dependence plots for highest importance variables
Importantly, LiDAR derived variables were shown to be more important than vegetation management and soil/terrain variables.

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