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Article

The Impact of Visual Defects and Neighboring Trees on Wind-related Tree Failures

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Abstract: Urban trees are often more sun- and wind-exposed than their forest-grown counterparts. These environmental differences can impact how many species grow – impacting trunk taper, crown spread, branch architecture, and other aspects of tree form. Given these differences, windthrow models derived from traditional forest production data sources may not be appropriate for urban forest management. Additionally, visual abnormalities historically labeled as “defects” in timber production may not have a significant impact on tree failure potential. In this study, we look at urban tree failures associated with Hurricane Irma in Tampa, Florida, USA. We used spatial analysis to determine if patterns of failure existed among our inventoried trees. We also looked at risk assessment data to determine which visual defects were the most common and the most likely to be associated with branch or whole-tree failure. Results indicate that there was no spatial pattern associated with the observed tree failures – trees failed or withstood the storm as individuals. While some defects like decay and dead wood were associated with increased tree failure, other defects like weak branch unions and poor branch architecture were less problematic.

Keywords: cyclone; defect; hurricane; likelihood of failure; storm damage; typhoon; urban ecology; urban forestry

1. Introduction

Throughout the world, urban developments are concentrated in coastal areas, many of which are exposed to intense wind events (e.g., hurricanes, cyclones, and typhoons) [1] that can induce failure of whole trees, branches, trunks, or roots. Previous work has investigated wind-induced tree failures in natural areas and on plantations [2 -8] as well as in urban areas [9-15]. In a recent systematic review, van Haaften et al. [16] conducted a meta-analysis of 161 studies that revealed 142 factors associated with tree failure. Measures of tree size (height, weight, volume, diameter at 1.4 m above ground (DBH)) were positively correlated with stem and root failures [16], but Klein et al. [17] found a negative correlation between tree size and likelihood of failure. Part of the inconsistency may have been due to the inclusion of studies that considered both forest- and open-grown trees in the meta-analysis. Natural forests lack many of the species commonly planted in urban and suburban areas [17] and open-grown trees are morphologically different from congeners growing in forest stands [18]. Branch failures are rarely reported in forest stands—and the meta-analysis found no positive relationships with independent variables [16]—but often make up a sizable proportion of failed trees in urban and suburban areas [9-10, 14, 17, 19-20]. Trees growing in urban and suburban landscapes also

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frequently have structural defects that can increase the likelihood of failure, although few studies [19, 21] have assessed the effect of defects.

In addition to intrinsic factors such as species, size, and the presence and severity of defects, wind is an important determinant of the likelihood of failure [10,14]. Summarizing the findings of survivability of sixteen species across eight different hurricanes, Klein et al. [17] reported a general decrease in survivorship as wind speed increased. In addition to mean wind speed recorded at a weather station, local wind speed can be influenced by topography, engineered structures, and surface cover [21], making it difficult to detect patterns that manifest in the likelihood of tree failure. For example, although Duryea et al. [14] noted that trees growing in groups were less likely to fail—presumably because of the sheltering effect of neighbors—Landry et al. [20] found no correlation between likelihood of failure and the count of trees in a sample plot.

Structures and planted trees can alter wind flow in developed landscapes, increasing its speed (compared to the mean reported at a nearby weather station) in one location, while decreasing it in another. A classic example of sheltering crops and structures from the wind is the use of windbreaks [22]. Their effectiveness depends on their height, length, width, density, and orientation with respect to airflow. The particular combination of these factors influences the amount of leeward area that is sheltered and the proportional reduction in wind speed. The reduction in wind speed in the leeward direction generally decreases beyond twenty times the height of the trees that make up the windbreak.

Likelihood of tree failure may also depend on neighborhood-level factors, which can influence canopy cover. Previous studies have demonstrated the effect of lot size, the proportion of single-family residential homes [23], and building age [24-25] on canopy cover. These factors might also influence the volume of soil available for rooting, which influences the likelihood of uprooting [14-15]. Neighborhood-level effects also influence tree maintenance [26-27], which has been shown to influence the likelihood of failure [14-15, 17, 28].

The variety and complexity of factors that influence the likelihood of tree failure make assessment a challenge. Practitioners have developed best practices to reduce uncertainty [29-31], but their reliability and accuracy are questionable [32]. Recent work has shown that if the likelihood of failure rating (using the International Society of Arboriculture Tree Risk BMP) was “imminent,” the likelihood of failure was positively related to the rating; but for lesser ratings such as “possible” and “probable,” the relationship was less clear [19].

Understanding wind-induced tree failures in urban areas is important because recent climate change reports have predicted that natural disasters (i.e., extreme wind events, drought, fires, and pest outbreaks) will increase in intensity and frequency [33-34] and that such disasters are a threat to canopy cover across the urban forests of the world [34].

Our objectives for this study were as follows:

1. Assess the accuracy of visual assessments of likelihood of failure using the United State Department of Agriculture Forest Service tree risk assessment method [29].
2. Determine which defects significantly contribute to whole and partial tree failure.
3. Assess whether the presence of a windbreak effect exists within the urban forest context.

2. Materials and Methods

2.1. Data Sources

In 2015, we conducted a complete inventory of street and park trees (n = 2,394) in three neighborhoods in Tampa, Florida, USA: Hyde Park (27.9417° N, 82.4639° W), South Seminole Heights (27.9888° N, 82.4621° W), and V.M. Ybor (27.9705° N, 82.4442° W). Estimated canopy cover in Hyde Park, South Seminole Heights, and V.M. Ybor is 42%, 47%, and 33%, respectively [35].

A pair of International Society of Arboriculture (ISA) Certified Arborists holding the ISA Tree Risk Assessment Qualification (TRAQ) conducted the inventory. Table 1

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includes data they collected, grouped by the following tree attributes: location, size, defects, and likelihood of failure rating. The likelihood of failure rating and assessment of defects were made in accordance with Pokorny [29]. If more than one defect were present, assessors recorded them and judged which was the most likely to cause failure.

In September 2017, Hurricane Irma made landfall in Southwest Florida as a category 3 hurricane. As the storm moved northward, it diminished in strength. By the time it reached the study sites in Tampa, Irma was downgraded to a category 1 storm [20] on the Saffir–Simpson Hurricane Wind Scale [36], which categorizes hurricanes, in part, based on the damage they can inflict on structures and trees. Category 1 hurricanes will cause "large branches of trees [to] snap and shallowly rooted trees may be toppled" [36].

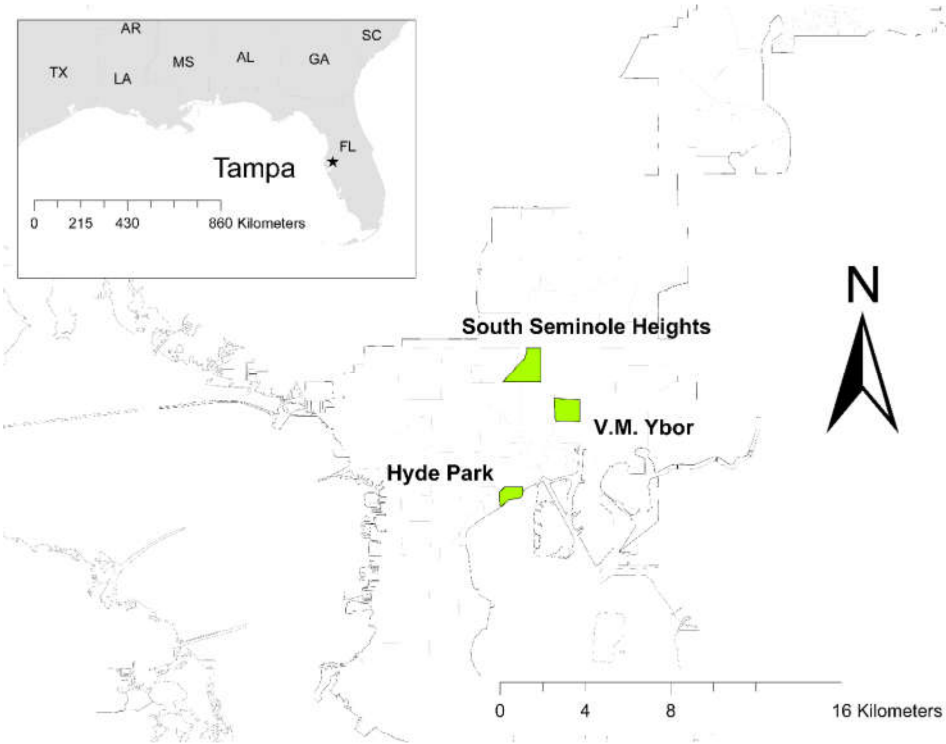

Figure 1. Study locations within the City of Tampa, Florida, USA. A complete tree inventory (see Table 1) was conducted within each of the three neighborhoods in 2015. In 2017, Hurricane Irma impacted the city as a category 1 storm on the Saffir-Simpson Hurricane Wind Scale. .

In the winter and early spring of 2018, we revisited the neighborhoods to assess storm damage. Two assessors, one of whom participated in the pre-hurricane inventory, searched for missing trees (determined by recently cut or ground stumps) and trees with broken branches or recent pruning cuts (determined visually from wood color and absence of woundwood formation). Since it was not possible to assess storm damage immediately following the storm for safety and to avoid impeding emergency cleanup operations, the assessors classified trees as standing, branch failure, or whole tree failure. It was not possible to determine whether whole tree failures were the result of root failure, stem failure, or sufficient crown damage that warranted removal.

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Table 1. Tree attributes recorded during the inventory of public trees in Tampa, Florida three years prior to Hurricane Irma. Variables used in our initial model to predict tree failure are **bolded.** .

Attributes	Variable (Type)	Definition
Location	Coordinates (continuous)	Latitude and longitude
	Street Address (nominal)	Street address
Size	Species (nominal)	
	DBH (continuous)	Stem diameter measured 1.4 m above ground
	Height (continuous)	Distance from ground to top of tree crown
	Height to lowest branch (continuous)	Distance from ground to lowest branches
	Crown width (continuous)	Mean distance of the north to south and east to west crown diameters measured along the ground.
Risk	**Likelihood of Failure Rating (ordinal)**	1=low, 2=moderate, 3=high, 4=extremely high
Defects[z]	Canker (binary)	Presence or absence of an area of dead bark and cambium.
	Crack (binary)	Presence or absence of a separation of the wood or a split through the bark into the wood.
	Dead (binary)	Presence or absence of a dead tree or dead wood within a tree.
	Decay (binary)	Presence or absence of rotted or missing wood.
	Poor Architecture (binary)	Presence or absence of a growth pattern indicating structural imbalance or weakness in the crown.
	Root Problems (binary)	Presence or absence of a root system providing inadequate anchorage. Could be further specified as "grade change," "planting depth," "sidewalk buckling," or "stem gridling."
	Weak branch union (binary)	Presence or absence of an epicormic branch or branch attachment with included bark.

[z]If more than one defect were present, assessors judged which was the most likely to cause failure.

2.2. Defect Analysis

We used chi-square tests to assess the significance of associations between tree defects (Table 1) and branch or whole-tree failures. The defects "canker" and "crack" were excluded from the analysis due to small sample sizes (n = 1 and 8, respectively).

2.3. Analysis of Sheltering

We used previously-generated land cover raster data of the City of Tampa [35] to assess the potential wind protection offered by neighboring trees and structures. The land cover used six classes derived from the National Land Cover Database (NLCD) classification system: bare earth, buildings, grass/shrub, impervious, water, and tree canopy. The raster data was at a 6-inch cell resolution and covered the entire Tampa city limits. For computational tractability, we buffered the three target neighborhood polygons by 500 meters and cropped the raster to these borders.

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To assess the possible sheltering effect of nearby aboveground structures, we classified land cover types buildings and tree canopy as "windbreak." The percentages of windbreak cover in buffers surrounding individual trees were calculated within buffers from 10 – 100 meters, in 10-meter intervals. To choose an appropriate buffer size, we selected the buffer size that maximized the variance in windbreak percent [37]. The variance was maximized at 10 meters; the percentage of windbreak within a 10 meter radius of individual trees was included as a covariate in the regression models.

2.4. Variable Selection and Modeling

Prior to creating models, we selected a set of candidate predictor variables from the data set: DBH, crown length (tree height – height to lowest branch), height ratio, canopy width, zoning (residential/commercial), likelihood of failure rating (1-4), neighborhood, and proportion of windbreak in surrounding buffer. A logistic regression model was fit using the glm() function in R [38] using tree failure as a binary response. A tree was considered to have experienced a failure if it was rated as either 'branch' or 'whole tree' failure in the survey. We eliminated crown length, and canopy width given either (i) high multicollinearity, as measured by variance inflation factor (VIF) > 4, or (ii) large numbers of missing data. In a further round of model selection, insignificant terms (apart from the windbreak) were removed leaving likelihood of failure and DBH as significant predictors. The windbreak term, although insignificant, was retained in the model because it was part of our third hypothesis.

We used the Moran's I statistic to test for spatial autocorrelation in the model residuals. To detect spatial autocorrelation, we created neighborhoods based on both distance-based and K-nearest-neighbor (KNN) methods using the knearneigh and dnearneigh functions in package spdep [39]. KNN neighborhoods were defined as the 5 nearest neighbors, while distance neighborhoods consisted of all trees within 150 m of a central tree. We used the moran.test() function in spdep [39] to perform the Moran's I tests.

Due to significant spatial autocorrelation in the logistic model residuals, a spatial autoregressive logistic model, hereafter referred to as the spatial GLS, with a Matérn correlation structure was fit using the fitme() function in packages spaMM [40]. A Matern process models clustering of like values in a point pattern; inclusion of an explicit Matern process model in a regression can remove spatial autocorrelation in the residuals. Significant residual autocorrelation violates the independence of observations model assumption and can result in unreliable estimates of the significance in model terms [41]. There was no significant spatial autcorrelation detected in the residuals of the spatial GLS. Conservative estimates of p-values were made by computing the p-values associated with the model terms' t-values. The p-values were calculated using 100 degrees of freedom (the final spatial GLS was built from 1979 observations.). P-values were then adjusted for multiple testing using the Hochberg method.

3. Results and Discussion

3.1. Tree Failures

Of the trees surveyed in 2015 in Hyde Park, South Seminole Heights, and V.M. Ybor, 25% failed: 18% branch failures and 7% whole tree failures. The overall failure rate was similar to that in Naples, Florida, USA, where Hurricane Irma (with winds from Category 1 to Category 2) caused 26% of surveyed trees to fail [17]. Following Irma's northward passage (as a tropical storm) through Tampa, Orange County, and Gainesville, Florida, Landry et al. [20] reported 20 whole tree failures and 376 branch failures among 693 trees. Their results are not directly comparable, however, because (i) they observed multiple branch failures in some trees and (ii) their sample included trees on private property and homeowners are willing to maintain trees in poorer conditions than managers on public, institutional, or commercial sites [35]. Only 7% of trees surveyed on institutional or commercial sites in Charleston, South Carolina, USA and Savannah, Georgia, USA failed during Tropical Storm Matthew in 2016 [19].

Likelihood of failure ratings are qualitative categorizations intended to cover all possible failure scenarios ranging from the highly unlikely to the nearly guaranteed. In the USDA Forest Service method [29] that we used for this project, ratings of 1, 2, 3, and 4 refer to "low," "moderate," "high," and "extremely high" likelihood of failure, respectively. Figure 2 shows the proportional distribution of sampled trees by likelihood of failure rating and failure type. Consistent with Koeser et al.'s [19] findings with a different 4-point rating system, most trees had a "low" (39%) or "moderate" (32%) likelihood of failure; only a small proportion of trees had an "extremely high" (5%) likelihood of failure (Figure 2). Approximately 24% had a "high" likelihood of failure. There is also a general increase in failures as likelihood of failure rating increases (Figure 2). The branch failures were similar for trees rated as having low, moderate, and high likelihood of failure, but much greater for trees rated as having an extremely high likelihood of failure. The proportion of branch failures was similar among the trees assessed as having "moderate" (19%), "high" (26%), and "extremely high" (28%) likelihoods of failure, but much smaller for trees with a "low" likelihood of failure (10%) (Figure 2). The proportion of whole tree failures was similar for trees with "low" (3%), "moderate" (7%), and "high" (7%) likelihoods of failure. However, 28% of trees rated as having an "extremely high" likelihood of failure were removed following the storm.

Figure 2 also reveals the nearly identical proportions of trees (i) assessed as having "moderate" and "high" likelihood of failure and (ii) in each failure type. Interestingly, both the number of trees rated as having "moderate" likelihood of failure (n=762) and "high" likelihood of failure (n=584) and the proportion of "whole", "branch", or "none" failures within each of these ratings were very similar (Fig. 2). This may be an indication of spurious resolution – or a rating system that has too many levels that are not distinct enough to warrant the existence of all of them [42]. In contrast, Koeser et al. [19] documented significant differences in rates of tree failure for all four levels of likelihood of failure using the approach described by Smiley et al. [31]. Beyond slightly differing terminology, the two risk assessment methods used are noticeably different in how they qualify likelihood of failure. The method used in this study [29] has a somewhat formulaic rating system based on the presence or absence of key defects and their severity (based, in some instances, on the proportion of the tree part affected). In contrast, the method assessed by Smiley et al. [31] gives the assessor more flexibility to draw on professional judgement – with most defects having a range of potential likelihood of failure ratings associated with them in the methods manual [30].

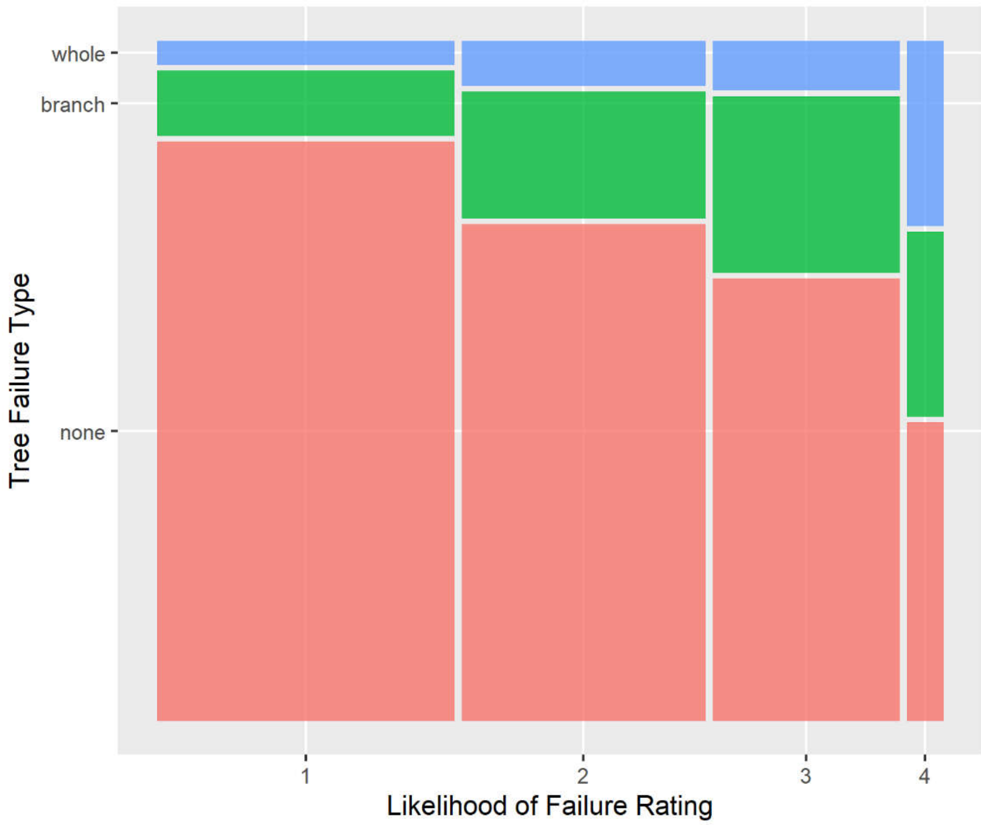

Figure 2. Mosaic plot showing the proportional distribution of failure types and likelihood of failure ratings of trees surveyed in 3 neighborhoods in Tampa. Ratings of 1, 2, 3, and 4 indicate "low," "moderate," "high," and "extremely high" likelihood of failure, respectively [29]. Chi-square test on the corresponding contingency table was highly significant (p-value < 0.001).

3.2. Defect Analysis

Assessing defects is integral to tree risk assessment as most systems attribute their presence with an increased likelihood of failure [30–31]. This noted, some defects have received more empirical scrutiny than others. Many studies have investigated how well practitioners can assess the presence, extent, and location of decay [43-46}; fewer have explored the degree to which decay increases the likelihood of failure [19, 47]. In this study, the presence of decay was associated with a greater proportion of branch and whole tree failures (Figure 3), but Koeser et al.'s [19] data did not align with this, which is a reminder that the presence of even a severe defect does not always induce failure.

Another commonly assessed defect is weak branch attachment, the most commonly reported defect in our data (Figure 3). As might be expected given their location in the tree, weak branch attachments were associated with a smaller proportion of whole tree failures (Figure 3). And although many studies have quantified the reduced load-bearing capacity of weak branch attachments [48 – 51], they did not fail in 78% of trees in which they were the defect of primary concern. The comparatively low failure rate of weak branch attachment aligned with previous studies of tree failures following a hurricane [19] and a snowstorm [47], suggesting that it may not be as serious a defect as considered.

Other commonly reported defects in our study were dead branches and poor architecture (Figure 3). When dead branches were present, the proportion of branch failures was greater (p-value < 0.001, Figure 3), which we expected and aligned with previous work [19]. But it was unexpected that there were fewer branch failures—and a smaller proportion of failures overall—associated with trees that had poor architecture (p-value < 0.001, Figure 3). The findings do not align well with Koeser et al.'s [19] results, illustrating

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the challenge of assessing defects and the overall uncertainty of assessing likelihood of failure.

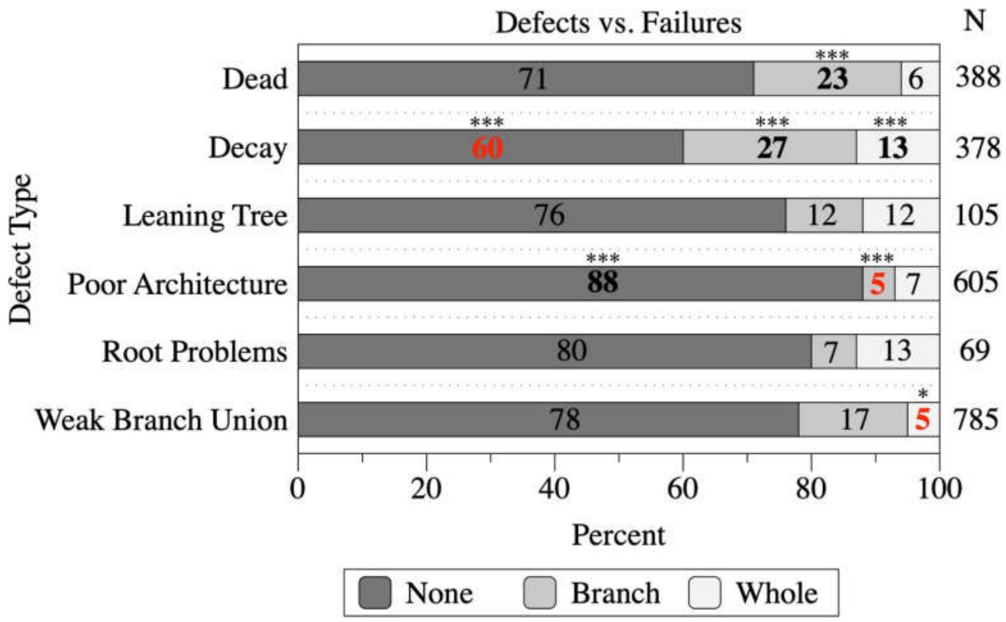

Figure 3. Percentage of trees that did not fail ("None") and those that experienced branch or whole-tree failure categorized by defects present before the passage of Hurricane Irma. Values in black, boldface type are higher than expected given the null hypothesis that defects do not influence the likelihood of failure. Values in red, boldface type are lower than would be expected given the null hypothesis that defects do not influence the likelihood of failure. A single asterisk (*) indicates p-value ≤ 0.05; three asterisks (***) indicate p-value ≤ 0.001.

The uncertainty surrounding which defects truly limit a trees ability to weather a storm is highlighted in Table 2. This table summarizes the effects of defects on likelihood of failure from our work and two previous [19, 55] studies. The three studies used different assessment methods so direct comparison is not possible, but it is notable that only two defects (decay and dead branch or tree) were positively associated with likelihood of failure in more than one of the four studies. And one defect (weak branch attachment) was negatively associated with likelihood of failure in two of the studies. Other defects were positively (decline, lean, wound) or negatively (poor architecture) associated with likelihood of failure in a single study. Future studies should continue to assess the effect of defects on likelihood of failure; using the current industry best practices guide [31] would help record consistent defects, facilitating future analyses.

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Table 2. Defects assessed and associated with wind-induced tree failures from previous studies; red highlighting indicates that a defect was associated with increased tree failure (+) in two studies; orange highlighting indicates that a defect was associated with increased tree failure in one study; blue highlighting indicates that a defect was associated with decreased tree failure (-) in two studies; light gray highlighting indicates that a defect was associated with decreased tree failure (-) in one study; yellow highlighting indicates that a defect has not been associated with tree failure (NS); "•" indicates that a defect was not assessed in the study.

Defect	Hickman et al., 1995	Koeser et al., 2020	Current Data
Butt (wounds/missing bark/decay)	NS	•	•
Cavity	•	NS	•
Codominant stems	•	NS	•
Dead	•	+	+
Decay	+	NS	+
Decline/low live crown ratio	+	NS	•
Leaning tree	+	NS	NS
Limbs (wounds/missing bark/decay)	NS	•	•
Lion's tail	•	NS	•
Overextended branches	•	NS	•
Poor architecture	•	NS	-
Roots (exposed/girdled/cut)	NS	•	•
Sweep	•	NS	•
Uneven crown	•	NS	•
Weak branch attachments	•	-	-
Wound	•	+	•

3.3. Analysis of the Spatial GLS

The Moran's I test found significant spatial autocorrelation in the aspatial regression (p-value < 0.001), however this autocorrelation disappeared in the spatial GLS model (p-value > 0.05). In the spatial GLS, the coefficients for "medium", "high", and "extremely high" failure likelihood were all highly significant (p-value < 0.01). Higher likelihood of failure ratings was associated with increased tree failure rates; the coefficients for "medium" and "high" were similar (0.61 and 0.66, respectively), while the coefficient for "extremely high" was much higher (1.06). Larger DBH was associated with increases in likelihood of failure (p-value < 0.001), while the percentage of windbreak within 10 m of individual trees was not significant.

Table 3. Model coefficients for spatial GLS logistic regressions. Significance codes: *** p-value < 0.001, ** p-value < 0.01, * p-value < 0.05, n.s. not significant.

Coefficient	Estimate	Standard Error	t-value
Intercept	-2.79	0.14	-19.87***
Failure Likelihood 2	0.61	0.17	3.54**
Failure Likelihood 3	0.66	0.18	3.65**
Failure Likelihood 4	1.06	0.32	3.34**
DBH	0.07	0.01	11.48***
Windbreak	-0.02	0.07	0.07 (n.s.)

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4. Conclusions

This work offers further evidence that visual tree risk assessment by trained assessors can be used to predict tree failure associated with wind events. Increased branch and whole tree failures were associated with the more severe ratings of failure potential. This noted, there could be issues of spurious resolution (to many levels) in the system used as the middle two ratings had similar failure profiles. While visual defect assessment is core to most assessment methods, our results support past findings which indicate that only a portion of the issues arborists and urban foresters include in their assessments are associated with increased rates of failure during storms. More research is needed to determine which defects are categorized as such given their impact on tree structural integrity. Moreover, research is needed to determine when strength reduction becomes problematic with regard to trees and expected wind loads

Author Contributions: Conceptualization, AKK; Methodology, AKK; Formal analysis, MFN; Data curation, AKK and MFN; Writing – Original draft, AKK, RWK, BK and MFN; Writing – Review & editing, AKK, MFN, RWK, BK, and SML; Visualization, AKK and MFN; Supervision, AKK; Project administration, AKK; Funding acquisition, AKK, BK, and SML.

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Data Availability Statement: Data is available upon request from the corresponding authors. Given the nature of the data (tree risk assessments in populated areas), address and location information will be stripped from the dataset prior to sharing.

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