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Expanding a Hurricane Wind Resistance Rating System for Tree Species

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Abstract: Background: Hurricanes and other wind events are significant disturbances that affect coastal urban forests around the world. Past research has led to the creation of wind resistance ratings for different tree species which can be used in urban forest management efforts to mitigate the effects of these storms. While useful, these ratings have been limited to species common to one global region (Florida, USA). Methods: Drawing on past ratings and data from a global literature review on tropical storm research, we created a machine learning model to broaden both the geographic coverage and the variety of species currently assessed for their resistance to wind. Results: We were able to assign wind resistance ratings to 281 new species based on the available data and our modelling efforts. The model accuracy and agreement with the original ratings when applied to the testing data set was high with 91% accuracy. Conclusions: The resulting list of wind resistance ratings has been adapted into a spreadsheet-based decision aid for managers, allowing them to assess the overall susceptibility of their urban forest to wind events like hurricanes.

Keywords: cyclone; risk management; species selection; tree failure; typhoon

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Introduction

Hurricanes profoundly impact coastal communities and their urban forests. Extreme winds and flooding directly damage trees by breaking branches, knocking trees over, snapping trunks, or causing stress from prolonged inundation or salt exposure (e.g., Wang et al. 2000; Wiersma et al. 2012; Middleton 2016). In turn, broken trees can damage property and infrastructure, contributing to power outages and hindering emergency operations (Yum et al. 2020; Taylor et al. 2022). During cleanup after a hurricane, tree-generated debris removal can increase cleanup costs, significantly increasing the ecosystem disservices generated by the urban forest. For example, in Florida the 2004-2005 hurricane season produced an average of 233 m^3 of debris per kilometer of street (Staudhammer et al. 2009). Furthermore, the cleanup process itself can lead to injuries among residents and professionals (Marshall et al. 2018). Ultimately, the loss of urban trees leads to a loss of ecosystem services (Olivero-Lora et al. 2022) and the harm damaged trees can cause to people, infrastructure, and property can all increase the public's negative perception of trees (Wyman et al. 2012; Roman et al. 2020; Judice et al. 2021).

To mitigate some of the risks hurricanes pose to the urban forest, Duryea et al. (2007a, b) created a rating system that classified tree species based on their ability to resist hurricane wind damage.

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They based the rating system on observations of urban tree damage across Florida and Puerto Rico following the 2004-2005 hurricane season, encompassing 9 hurricanes. They also surveyed urban forest professionals in their region and asked them to estimate the wind resistance of common urban tree species (Cite). They combined the damage observations and expert opinions to rate 137 tree and palm species. This is the most comprehensive set of wind resistance ratings for urban trees, though the list focused on tree species common to Florida's urban areas. Yet, hurricanes and typhoons pose risks to urban forests in many other regions of the world (e.g., Cole et al. 2021), highlighting the need for an expansion of the Duryea et al. (2007a, b) rating system.

Everham and Brokaw (1996) also compiled a list of tree species damaged by catastrophic winds (hurricanes, gales, severe windstorms) based on a literature review. They reported low, medium, and high damage ratings for 242 tree species. However, ratings were reported as originally published by the cited authors. No attempts were made to standardize these ratings to allow for formal comparisons of wind resistance across the entire collection of species. Their approach resulted in some species receiving multiple ratings; for example, *Quercus virginiana* Mill. was documented in four studies and given ratings of low (twice), medium, and high damage. While a substantial body of work, Everham and Brokaw's collection only relied on damage observations from a wide range of forested environments and was not tailored to the conditions present in the urban forest. By contrast, Duryea et al. (2007a, b) designed their rating system explicitly for use by urban forestry professionals. As such, their rating system has been incorporated into planning documents such the City of Tampa, U.S.'s Tree Matrix (https://tampatreemap.org/tree-matrix).

Given both the utility and the limited geographic scope (e.g., Southeastern United States and the Carribean) of the work of Duryea et al. (2007a, b), our research aims to increase the number of tree species with wind resistance ratings beyond the original 137 species documented in their work. Since Duryea et al. (2007a, b) provided a limited description of the rating process and did not create clear definitions for each wind resistance category, we used a machine learning algorithm to mimic the original wind resistance rating system and create a model that could predict ratings for previously unrated species. We trained the model using a portion (70%) of the original Duryea et al. (2007a, b) tree species along with predictor variables such as intrinsic species traits, study site and hurricane characteristics, and observations of hurricane damage to a particular species. Once trained, we tested the model with other original species to validate its ability to produce similar ratings as the original system. Then we applied the model to previously unrated species with sufficient predictor data identified from a literature review. Finally, we combined the original and newly rated species into a spreadsheet tool for use by urban forestry professionals and community groups.

Methods

Predictor Selection

Many biotic and abiotic factors influence a tree's ability to resist damage from hurricane force winds (Salisbury et al. 2023). However, for the purpose of developing our predictive model, we limited our choice of predictors based on the availability of data within the studies identified in our literature review or within other databases. Some model variables represent generalizations of the species while others try to capture variation among study sites.

We used the proportion of a species' population damaged or killed by a hurricane as the most direct measure of a species' ability to resist hurricane damage. Duryea et al. (2007a, b) used the proportion of mortality as one factor when assigning wind resistance ratings to species.

Following observations from several hurricanes in Puerto Rico, Lugo (2008) hypothesized that tree growth rate could represent a hurricane response syndrome that includes architecture, elastic modulus (i.e. the ability to return back to its original shape when bent), successional status, and wood density. Of these traits, only wood density is widely and consistently documented. Species with denser wood, greater modulus of rupture (i.e., the ability to withstand bending) and modulus of elasticity can be more resistant to hurricane damage (Duryea et al. 2007a, b; Nakamura 2020, Francis 2000, Curran et al. 2008). Granted, other biotic and abiotic factors can moderate the effects of wood density (e.g. Paz et al. 2018; Uriarte et al. 2019). Wood density also strongly correlates with other wood properties and captures many aspects of wood functions (Chave et al. 2009).

Several researchers have observed greater rates of hurricane damage to early successional or pioneer species which tend to be fast growers (Zimmerman et al. 1994; Ostertag et al. 2005; Canham et al. 2010). Yet, without a consistent definition of early, mid, and late successional species across a range of biomes and continents, successional status did not lend itself to predictive modeling. Instead, we selected leaf mass per unit area as a proxy variable since it tends to correlate with shade tolerance or successional status (Wright et al. 2004; Reich et al. 2014; Lichstein et al. 2021). Generally, species with low leaf mass per unit area tend to be fast-growing and intolerant of shade, or early successional, while higher leaf mass per unit area species tend to be slow-growing and tolerant of shade – characteristics associated with late successional species.

We used maximum height potential (as reported in the literature) as a predictor since taller trees are often (Foster 1988; Johnsen et al. 2009; Xi et al. 2015), though not always prone to more damage (Gao and Yu 2021; Landry et al. 2021). Most of our data sources did not include height data, so we used maximum height to generalize results at the species level. Observations of multiple types of catastrophic windstorms suggest gymnosperms (conifers) tend to be less wind resistant compared to angiosperms (Everham and Brokaw 1996; Gardiner 2021). Similarly, deciduous or semi-deciduous trees may have an advantage in high winds compared to evergreen species though this effect has not been consistently observed (Everham and Brokaw 1996; Van Bloem et al. 2005).

Since some regions of the world and biomes are more prone to hurricanes than others, we included biome, latitude, and longitude in the model. Hurricane disturbance history may also influence a site's susceptibility to future hurricane damage in diverging ways: previous storms could remove susceptible trees leaving the population more resistant to future damage or gaps created by previous storms could expose remaining trees to additional turbulence in future storms (Everham and Brokaw 1996; Ostertag et al. 2005). To the best of our knowledge, no study has compared hurricane damage to tree species between urban and rural settings (i.e., trees in highly built environments and trees growing in large forest stands). Nevertheless, considering these are two distinct settings, we included urban or rural setting as a model variable to account for these differences among studies.

Systematic Literature Search

We conducted a systematic literature search to identify peer-reviewed research and dissertations that contained hurricane damage data at the species level. We searched for papers and dissertations published between 1900 and 2022 in English, Chinese (Mandarin), French, Japanese, Portuguese, and Spanish. We searched in several search engines and databases in addition to forestry-related journals that may not have been indexed in a particular database (see Supplementary Table S3 in Salisbury et al. 2023). The last search was conducted on May 5, 2022. Our core search string in English was "forest AND (hurricane OR cyclone OR typhoon)", its translation and synonyms in the five additional focal languages can be found in Supplementary Table S2 in Salisbury et al. 2023.

We screened the results of our search using the following criteria to include papers in the dataset: 1) data collection occurred within two years of a tropical cyclone; 2) the only disaster studied was a tropical cyclone or tropical storm; 3) researchers used ground-based methods of data collection, as opposed to techniques such as aerial surveys; and 4) the paper reported data at the species level as a proportion of a population or sample and provided the scientific binomial name of the species. We excluded mangrove ecosystems since these species are not typically planted in managed urban habitats.

We rated methodological completeness by answering the following questions for each study; did the study: 1) collect data using a randomized study design or by conducting a complete inventory? 2) report observations of damage based on the type of damage (e.g., broken branches, snapped trunk)? 3) conduct an assessment of the tree's condition or potential risk of failure? and 4) measure tree size? We assigned one point for each question that received a "yes," for a total potential score of 4.

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After screening, we extracted damage data and other relevant information from each study. When possible, we used Tabula (https://tabula.technology) to extract damage data in table form, otherwise we manually copied the data into spreadsheet form. We extracted data from figures using WebPlotDigitizer (https://automeris.io/WebPlotDigitizer/). For papers written in Spanish, Japanese, or Chinese, a multi-lingual team member checked the translation to English made by Google Translate. We also recorded the location of the study site, the tropical cyclone name, and method details using a spreadsheet. We classified damage data into one of four categories (Table 1) and each study as urban or rural. An urban study collected data within a city or town, either in a highly managed environment (e.g., street trees) or in a natural area located within an urban matrix. A rural study collected data within a natural area or timber plantation that had little to no potential impact from urban development. We excluded observations that were only made to the genus or family level.

Table 1. Damage categories and definitions used to classify data extract from the literature review.

Damage type	Definition
Mortality (%)	Trees considered dead.
All damage types (%)	Multiple types of damage that were combined (e.g., snapped trunks and uprooted).
Root failure (%)	Trees that fell over because root or root plate anchorage failed. Also described as tipped up, uprooted, or windthrow.
Stem failure (%)	Trees with broken or snapped main stem/trunk/bole.

Tropical Cyclone and Study Site Characteristics

We used data from the International Best Track Archive for Climate Stewardship (IBTrACS) to determine the maximum sustained wind speed for each tropical cyclone in our dataset (Knapp et al. 2010, 2018). This provided a consistent metric to compare studies using one facet of storm intensity. We also used IBTrACS to determine the amount of time that had elapsed between a study's tropical cyclone and the previous tropical cyclone that had passed within 50 km of the study site. We determined the biome of each study site using the typology developed by Olson et al. (2001). Note: although a territory of the United States, we counted Puerto Rico separately from other U.S. study sites because of its distinct tropical habitats not found in the continental U.S.

Tree Species Characteristics

Prior to extracting species' traits from several datasets (Table 2), the names of species identified in our literature review and species in the trait datasets were harmonized to the Leipzig Catalog of Vascular Plants taxonomic backbone (Freiberg et al. 2020) using the lcvplants package v.2.1.0 (Freiberg et al. 2020) in R v.4.2.2 (R Core Team 2022). We first harmonized species to the LCVP backbone using exact matching, then we used fuzzy matching for species without an exact fit. All fuzzy matched species were manually checked to ensure a reasonable match. When we could not match a species the LCVP backbone with reasonable certainty (many of the species did not include botanical authorities), we excluded the species from further analysis.

Table 2. Predictors used in the random forests model.

Predictor	Definition	Sources
Angiosperm or Gymnosperm	The tree type	Multiple
Biome	General habitat type at study location	Olson et al., 2001
Damage	Proportion of species that died or were damaged during a tropical cyclone	Original source of data
Latitude	Latitude of study site	Original source of data

Leaf Type	Leaf phenological type: evergreen or deciduous/semi-deciduous	Kattge et al. 2020
Leaf Mass Per Unit Area	Leaf mass per unit area in g/m^2	Kattge et al. 2020
Longitude	Longitude of study site	Original source of data
Maximum Plant Height	Mean height at maturity (m)	Moles et al. 2004; Kattge et al. 2020
Previous Tropical Cyclone	Time elapsed between the study's focal storm and the previous tropical cyclone occurring within 50 km of the study site	IBTrACs
Urban or Rural	General landscape setting of study	Original source of data
Wood Density	Mean wood density (ratio of dry wood weight to fresh volume; g/cm^3)	Zanne et al. 2009; Kattge et al. 2020

Many of the traits (e.g., leaf type, leaf mass per unit area, maximum plant height, and wood density) came from the TRY PlantTr database's publicly available data (Kattge et al. 2020, Table 2). Prior to the analysis, we removed TRY observations from experimental settings (e.g., growth chambers, glasshouses, etc.). We also removed TRY observations which had an error risk greater than 4, meaning that the trait value was more than four standard deviations away from the mean for other close relatives – as suggested by the database creators (https://www.try-db.org/TryWeb/TRY_Data_Release_Notes.pdf). Occasionally, a species had multiple trait values in a dataset. In those cases, we calculated the mean trait value for the species and used that value in our analysis. If a species had multiple leaf types, we either assigned the leaf type with the most observations or deciduous/semideciduous.

Model Development

We used a random forest classification procedure to create a model that could predict Wind Resistance Ratings for species based on observations of tropical cyclone damage and species characteristics. Random forests are a powerful and flexible nonparametric technique that does not make assumptions about data following a particular distribution (Breiman 2001, Cutler et al. 2007). Since random forests make predictions based on the consensus of hundreds of models, they generally produce models with low bias and variance which are considered to more accurate and consistent.

To create a random forest model that could predict species' wind resistance rating, we first collected all observations for the original tree species in Duryea et al. (2007a, b) which had a complete set of wood density, leaf mass per unit area, and maximum height trait data. We then randomly selected 70% of those observations for use as training data while the remaining 30% were test data. During the random selection process to split the data, we stratified data by wind resistance rating to ensure even representation of each classification group.

Model predictors included urban or rural setting, angiosperm or gymnosperm, time since previous tropical cyclone within a 50 km radius of the study site, the latitude and longitude of the study site, biome, leaf type, wood density, maximum plant height, leaf mass per unit area, and damage (Table 2). Observations were sparsely distributed between the four types of damage identified in the literature review (mortality, multiple damage types, stem failure, and root failure). Consequently, we consolidated the four damage types into a single variable (damage). After testing different permutations of the damage data, when multiple types of damage were reported for a single observation (e.g., mortality and root failure), we would first assign "multiple damage types" to the final damage value. If the observation lacked multiple damage types data, then we would use mortality data, followed by root failure, then stem failure.

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We fit a random forests model to the training data using the "rf" method of the *caret* package in R (Kuhn 2022). We set the model to contain 1,000 random forest trees and we used 10-fold cross validation with 5 repeats when fitting the model to reduce model variance. Model tuning indicated that the model should test 8 variables at each node in a tree.

We subsequently tested model performance using the test dataset to determine overall accuracy, adjusted Cohen's Kappa with equal weights to each response category using the *DescTools* package (Signorell et al. 2022), sensitivity, and specificity. Sensitivity is the ratio of true positives to all positive predictions while specificity is the ratio of true negatives to all negative predictions. These values were calculated for each wind resistance category. For example, the specificity of the Highest category would be the number of correctly classified Highest observations to the total number of all observations predicted to have a Highest rating. We assessed the importance of each predictor using *caret*'s "varImp" function, which calculates the total decrease in node impurity, measured by the Gini index, that results from splitting data on a given variable and then averages that decrease across all trees.

Model Application

After training and testing the final model, we applied it to new tree species identified in our literature review (Salisbury et al. 2023) that were not part of the original wind resistance ratings list (observations = 440, species = 281). Since only 43% of these species had a complete set of wood density, mature height, and leaf mass per unit area data, we utilized imputation with bagged trees (Towards Data Science, 2020) to estimate missing data values. Earlier model testing revealed that observations with imputed wood density or imputed leaf mass per unit area and maximum height did not produce reliable predictions. Consequently, observations with missing wood density or missing leaf mass per unit area and maximum height were excluded from the prediction process.

We evaluated the confidence of each classification by examining the predicted probability that an observation was assigned to a given Wind Resistance Rating. The greater the predicted probability, the greater the confidence in the classification. For ease of interpretation by future users, we assigned each species a categorical confidence rating of Low Confidence (predicted probability ≤ 0.33), Moderate Confidence (0.33 < predicted probability ≤ 0.66), or High Confidence (predicted probability > 0.66).

Many species had multiple observations of damage data from different studies and consequently each observation received a unique predicted rating. Only 18 species with multiple observations received more than one rating. For these cases, the species was assigned the rating with the highest predicted probability and was marked as having Low Confidence. In other cases where multiple observations for a species were all assigned the same rating, we assigned the species the confidence rating from the highest predicted probability.

We then combined the original and new species into a single table that serves as the foundation for the Estimating Tree Community Hurricane Resistance Tool (ETCHR, v.01). We created ETCHR v.01 as an Excel Workbook which can use our database of wind resistance ratings and a community's inventory data to estimate the proportion of wind resistant species in a tree population.

Results

Literature Search

The broad search terms produced 5,449 studies, of which 58 passed the screening process and had appropriate data for the study (Appendix Tables A1 and A2). We attribute the low percentage of retained studies to the extremely general search terms we used and the apparent inability of some databases we searched to effectively utilize Boolean operators. The final studies in English, Chinese, Japanese, and Spanish produced 1,094 observations of species-level damage data. The studies took place 15 countries and examined 42 unique tropical cyclones (Figure 2; Appendix Table A1). Out of the original collection of observations, 285 observations representing 213 species lacked sufficient trait data to be used in the study (Figure 1).

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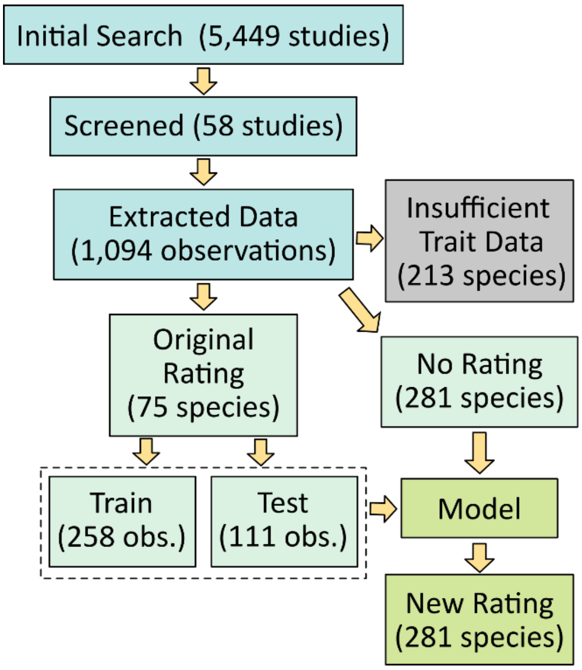

Figure 1. Wind Resistance Rating model development process.

Figure 2. The location of rural and urban study sites for papers with species-damage data identified in the literature search. Light blue lines indicate the paths of tropical cyclones that have made landfall since 1970.

Model Performance

We trained the random forest model using data from 73 species extracted from 39 studies and then tested the model using data from 52 species and 32 studies. Note that some species had multiple observations of damage. The model accuracy and agreement with the original ratings when applied to the testing data set was fairly high; accuracy was 0.91 while adjusted Cohen's Kappa was 0.91 (Table 3). Within the four ratings, the model performed best for Medium High and Highest species and performed more poorly for Lowest and Medium Low.

Table 3. Performance metrics for the testing dataset. Wind resistance rating accuracy across all data was calculated at 0.91 (0.84-0.96) with an adjusted Kappa of 0.91 (0.9-0.91).

	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value	Balanced Accuracy	Obs. Quantity
Lowest	0.83	0.98	0.92	0.94	0.9	29
Medium Low	0.9	0.93	0.88	0.94	0.92	42
Medium High	0.95	0.98	0.9	0.99	0.96	20
Highest	1	0.99	0.95	1	0.99	20

Wood density, maximum height, and leaf mass per unit area were the most important predictors in the random forest model (Figure 3). When one of those variables were included at a node, they were better at splitting the data so that subgroups contained observations with the same classifications. Percent damaged, latitude, and longitude were also moderately important predictors.

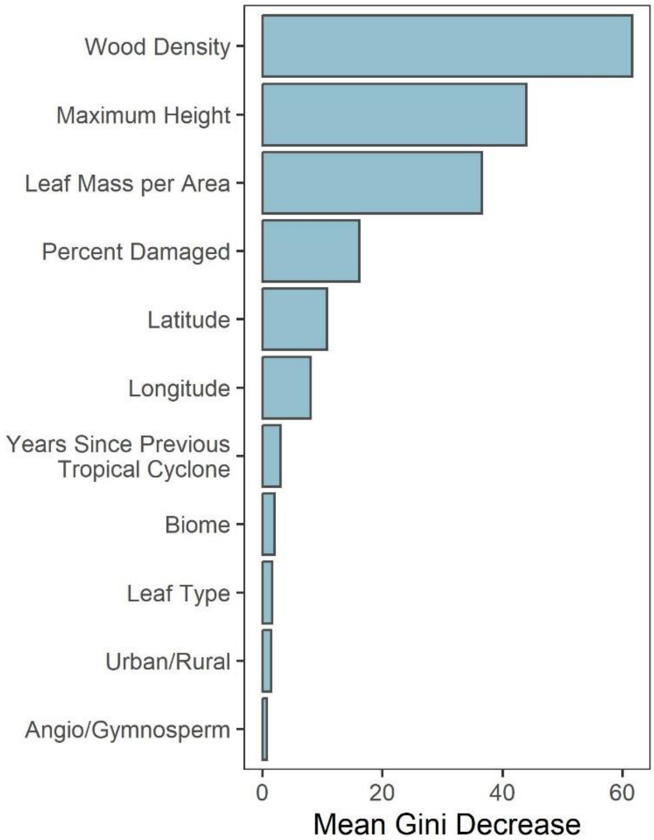

Figure 3. Variable importance scores for the model predictors. A greater Mean Gini Decrease indicates a greater importance in the model.

Species in the training and testing data set with a high or medium high rating tend to have greater wood density compared to those with lower ratings (Figure 4). By contrast, high species tend to have shorter maximum heights. The rating groups had similar average leaf mass per unit area, though the maximum leaf mass per unit area in the low group was much greater than the other groups. Unsurprisingly, the average extent of damage decreased with increasing wind resistance rating, though within all groups damage varied substantially. The wide variability of predictor variables within the ratings and lack of linear relationships highlight the value of using a classification based approach and the difficulty of relying on a single characteristic to predict wind resistance.

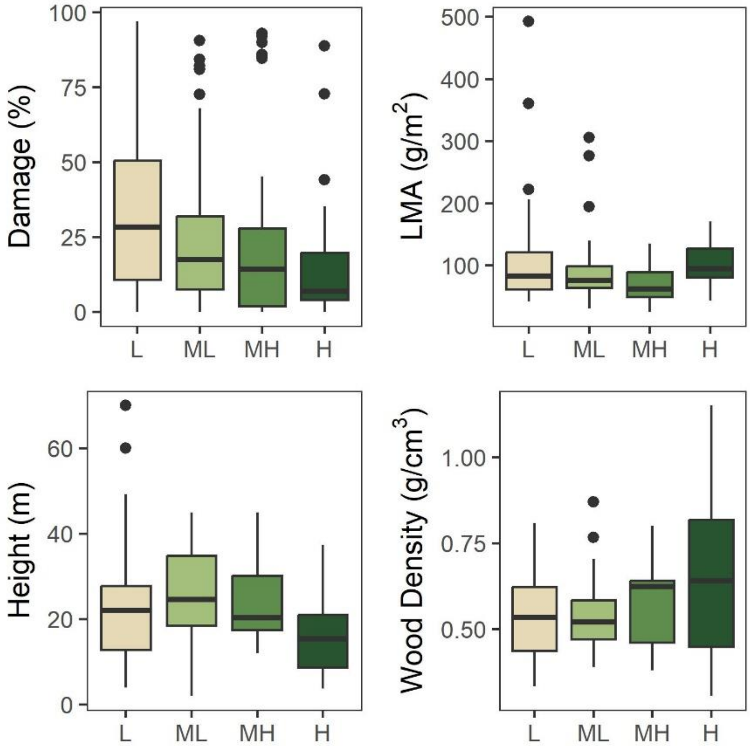

Figure 4. The distribution of percent damaged, leaf mass per unit area (LMA), maximum species height, and wood density among wind resistance ratings. Data from training and testing sets. L = low, ML = medium low, MH = medium high, H = high.

Ratings for New Species

We used the trained random forest model to assign wind resistance ratings to 281 new species we found in our literature search which had sufficient trait data (Appendix Table A2**;** data and original model also available at https://github.com/AllysonS/TreesForHurricanes). These species come from studies in the North Atlantic; Northwest and South Pacific; and North and South Indian tropical cyclone basins. They were studied in temperate conifer forests, tropical and subtropical moist broadleaf forests, tropical and subtropical dry broadleaf forests, and temperate broadleaf and mixed forests. Of these new species, 42% were assigned a low rating, 30% medium low, 14% medium high, and 14% high. both medium low and high wind resistance ratings had the greater proportion of species with high confidence in their predictions (23% and 21%, respectively, within each rating; Figure 5).

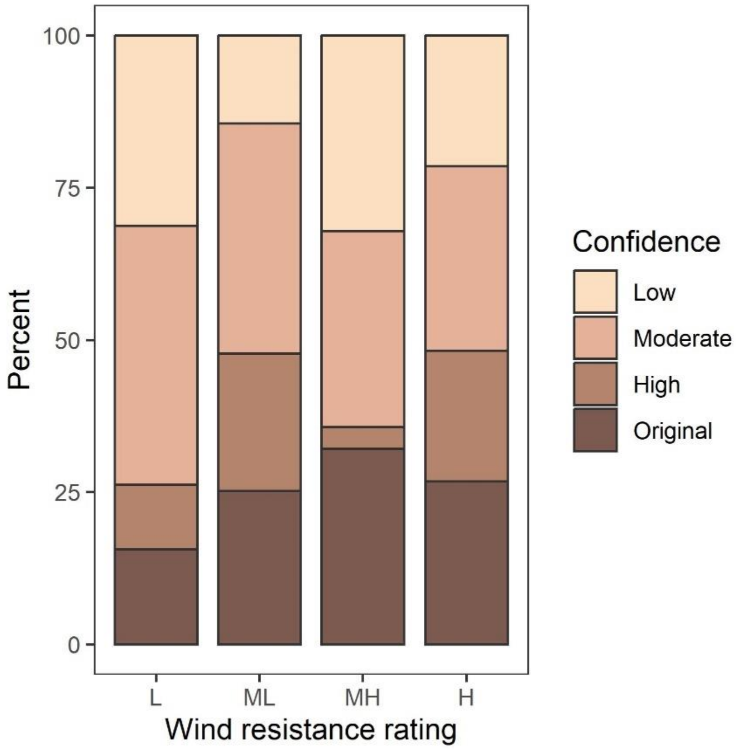

Figure 5. The proportion of Confidence Levels within each Wind Resistance Rating category.

Twenty-two species were assigned more than one wind resistance rating since those species had data from multiple studies and we allowed the model to assign different ratings to different studies. We gave each of these species their final wind resistance rating based on the rating with the greatest predicted probability, then classified the species as having low confidence. These multi-rating species accounted for 24% of species with low confidence predictions. The majority of the other low confidence species received that classification because one or more of their traits was imputed prior to prediction. Examples of species with multiple ratings include *Ficus religiosa* L. from China, India, and Sri Lanka (Dittus 1985; Sundarapandian et al. 2014; Guo et al. 2020; Lin et al. 2017; Zhou and Dong 2018; Wang et al. 2000); *Ginkgo biloba* L. from Japan (Tabata et al 2020; Nakamura 2020); and *Schefflera morototoni* (Aubl.) Decne. & Planch. from Puerto Rico (Zimmerman et al. 1994; Francis 2000).

Tree Community Tropical Cyclone Resistance Calculator

We combined the newly rated species with the original ratings list into a spreadsheet tool (with associated guide and video tutorial) called the Estimating Tree Community Hurricane Resistance Tool (ETCHR, v.01, https://github.com/AllysonS/TreesForHurricanes). A community with a tree inventory can add their list of tree species and quantities into the "DataInput" tab of the spreadsheet. The Tool identifies the Wind Resistance Rating of the species from the inventory list and then calculates the proportion of the tree population that has Lowest, Medium Low, Medium High, and Highest ratings ("Summary" tab). Recognizing that tree resistance to tropical cyclone damage may vary by location and that new ratings may be inconsistent with practitioner experiences in different regions, the Tool gives users the option to adjust the rating based on local experience.

To provide an example application of the ETCHR Calculator, we evaluated three i-Tree inventories conducted in the City of Tampa, FL, USA in 2016 and 2021 (Table 4). The 2016 and 2021 inventories show consistent proportions of wind resistant species during this five-year period.

Table 4. The percentage of trees in each wind resistance rating category from the City of Tampa's 2011, 2016, and 2021 i-Tree inventories determined using the ETCHR Tool.

Wind resistance rating	2016[Y]	2021[Z]
Lowest	11%	6%
Medium low	17%	17%
Medium high	9%	6%
Highest	23%	20%
Unknown	40%	51%
Total Estimated Trees	9,234,900	10,401,415

[z]Landry et al. 2023. [y]Landry et al. 2018.

Discussion

Our analysis of the original rated species and new species demonstrated that our random forest model is a reasonable approach for predicting wind resistance ratings that align with original work by Duryea et al. (2007a, b). The random forest approach allowed us to accommodate many predictor variables which often had non-linear relationships with ratings groups (Figure 4). And importantly, the predictive model can be applied to other new species as trait and tropical cyclone damage data become available. It is possible that adding additional predictors could have further increased the performance of the model with the training data, however, trying to further improve model accuracy could have overfit the model and reduced its predictive capabilities (Kuhn and Johnson 2013).

The high importance value of wood density indicates that our model aligns well with the original Duryea et al.'s ratings. Wood density is a commonly reported trait and was one of the key tree characteristics that Duryea et al. (2007a, b) analyzed and considered in their determination of the ratings system. Other wood anatomy traits such as the modulus of rupture and wood fiber width can also predict tropical cyclone tree damage and other wind-based tree failures (Xu et al. 2014; Nakamura 2020; Gardiner 2021). However, for the purposes of prediction, wood density is a more widely reported trait and tends to be directly related to other wood characteristics (Chave et al. 2009). That noted, wood density and other mechanical properties and crown traits can vary within species that have broad ranges with varying exposure to windstorms (Cannon et al., 2023; Plourde et al. 2015).

The high importance values for leaf mass per unit area and max height emphasize that our predictive model is primarily driven by intrinsic characteristics and represents generalized predictions about species' abilities to resist wind damage. The original rating system incorporated expert opinions, which provided substantial value to the rating system by capturing a broader range of experiences beyond the post-storm data collected by researchers (Duryea et al. 2007a, b). However, that approach was challenging to replicate for a large number of new species. Rather than directly incorporating expert opinions into the new predictive model, we incorporated a function in the ETCHR Tool to allow users to adjust the wind resistance rating based on expert knowledge of local conditions and species. In this way, our extension of the original rating system serves as a foundation for professionals to build on and tailor to their local environment.

There are several ways communities can utilize the wind resistance rating system to increase the resilience of their urban forests in the face of future tropical cyclones. Such activities can be considered mitigation, actions which preemptively eliminate or decrease the potential harm from a natural disaster (FEMA 2023). Many urban forestry and urban greening practices can facilitate recovery after natural disasters and with careful planning foster more resilient communities through recovery efforts (Campbell et al. 2019).

Many communities use urban forest management plans to set goals such as the extent of canopy cover or the diversity of tree species (Hauer and Peterson 2016). Output from the ETCHR Tool could be used to set and track goals related to the proportion of Medium High and *High* wind resistance rating species within a town or city. These goals could be achieved by incorporating Medium High and High species into new planting projects. Wind resistance ratings could be incorporated into forest climate change vulnerability assessments (e.g., Brandt et al. 2016). Many organizations use

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recommended species lists with details about site tolerances and species characteristics to encourage community members to plant the right tree in the right place (e.g., New York City Parks 2023; USF Water Institute 2023). Adding wind resistance ratings to such lists could help community members consider this characteristic when planting new trees.

Granted, the goal should not be achieving a tree community with 100% Medium High and *Highest* species as lower rated species are important in urban and rural forests. Indeed, maintaining functional diversity – a collection of species with a broad range of traits or characteristics – in urban forests minimizes vulnerability to changing climate and pest and disease outbreaks (Paquette et al, 2021). And in natural areas, fallen trees create gaps where younger trees establish, playing an important role in the life of the forest (Lugo 2008). Priority could be given to planting *Medium High* and *High* species in locations with high occupancy or high value targets, such as infrastructure or busy streets (Ellison 2005).

Conducting risk assessments and proactively pruning trees also contribute to mitigating hurricane damage to trees (Gilman et al. 2008; Koeser et al. 2020; Nelson et al. 2022). While resources for urban forestry programs can be limited compared to their needs (Hauer and Peterson 2016), wind resistance ratings could be used to complement other high volume risk assessment methods such as windshield surveys to identify trees with a high likelihood of failure (Rooney et al. 2005).

One drawback of the original rating system is the assignment of four wind resistance categories. Ideally, risk matrices clearly distinguish between very high and very low risk conditions but increasing the number of risk categories can muddy such distinctions (Cox 2008). And indeed, the properties of species in the *Medium Low* and Medium High categories tend to be similar (Figure 4). We maintained the original four categories to maintain consistency with the original research, though depending on local conditions, practitioners may find utility in combining the Medium Low and Medium High categories.

The application of the ETCHR Tool to the City of Tampa's i-Tree inventories (Landry et al. 2023) demonstrates its potential in urban forest management as well as the need to continue expanding the wind resistance rating system to additional species since substantial portions of the inventories did not have wind resistance ratings. Notably, mangrove species, which lack wind resistance classifications, constituted a larger proportion of the 2011 inventory compared to 2016 and 2021 (50% versus 18% and 31%, respectively). This explains the larger percentage of trees with unknown wind resistance ratings in 2011. Because mangroves occupy coastal areas that bear the brunt of incoming storm surge (Sherman et al. 2001) and because they were not included in the original Duryea et al. (2007 a, b) rating system, we excluded them from our random forest model. Nevertheless, mangroves play an important role in subtropical and tropical coastal ecosystems (Barbier et al. 2011) and warrant further investigation to bring them into this wind resistance rating system.

To collect as many examples as possible to train a robust model, many of the species in this study come from rural settings and are not in nursery production. Nevertheless, the advantage of our modeling approach is that when data becomes available for unrated urban species, the model can use that new data to rate those species. Other research needs on this topic include examining the interaction between species' wind resistance ratings and pruning techniques, and further evaluating the efficacy of practices intended to mitigate hurricane damage to urban trees.

While our work expands and helps synthesize past research on the wind resistance of trees, there are still gaps in our understanding. The literature referenced remains dominated by research published in English and focused on study sites in the Atlantic Ocean and Carribean Sea. The south Pacific is currently underrepresented, and we were unable to find research that met our criteria from Madagascar (Figure 2).

Finally, Duryea et al. (2007a, b) combined their post-hurricane field observations with a survey of the professional experiences of urban tree managers. It will be interesting so see if the predictions of our model reflect what our audience has witnessed in their post-storm cleanup efforts. We appreciate any feedback from readers who have worked in hurricane-prone areas.

Conclusion

Duryea et al. (2007a, b) developed a wind resistance rating system that arborists and urban foresters have used as a planning tool to improve species selection and identify species at greater risk of failure during hurricanes. In this paper, we demonstrated how a random forests predictive model can extend the original Duryea et al. rating system to include new tree species not observed in their original study. Our model assigned many new species a rating with moderate to high confidence, though ultimately future observations of hurricane damage to these species will support or refute these ratings. By sharing the model code, it can be adjusted to incorporate new data and further improve the rating system. We intend for our model and its interactive spreadsheet, ETCHR, to be an additional tool in the toolbox of urban forest hurricane mitigation strategies. As more storms occur in regions previously unstudied, our methods can be replicated to continue to expand our understanding or relative wind resistance ratings.

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Appendix

Appendix Table A1. The quantities of studies found by the literature search and passed screening criteria, in addition to the number of unique tropical cyclones observed in the studies and the countries or territories where the study took place.

Language	Search	Met Criteria	Observations	Tropical Cyclones	Countries/Territories
English	483	43	728	28	American Samoa, Australia, Hawaii, India, Japan, Mexico, Puerto Rico, Samoa, Solomon Islands, Sri Lanka, Tonga, conterminous U.S.
Chinese	97	9	199	8	China
French	140				
Japanese	3709	3	60	3	Japan
Portuguese	72				
Spanish	948	3*	107	3	Honduras, Mexico, Nicaragua
Total	5449	58	1094	42	15

* Note: One study was published in both Spanish and English.

Appendix Table A2. Research studies that documented hurricane damage to tree populations grouped by tropical cyclone basin. We used these studies as data sources for the predictive model.

North Atlantic	North Pacific	South Pacific
Basnet et al. 1992	Harrington et al. 1997	Burslem et al. 2000
Batista and Platt 2003	Bellingham et al. 1996	Elmqvist et al. 1994
Chapman et al. 2008	Guo et al. 2020	Franklin et al. 2004
Doyle et al. 1995	Huanglong 2002	Webb et al. 2014
Duryea et al. 2007a	Ida and Nakagoshi 1997	
Duryea et al. 2007b	Lin et al. 2017	
Francis 2000	Nakamura 2021	
Gao and Yu 2021	Saito 2002	**North Indian**
Gresham et al. 1991	Sato et al. 2009	Dittus 1985
Harcombe et al. 2009	Tabata et al. 2020	Sundarapandian et al. 2014
Henkel et al. 2016	Tian et al. 2020	
Howard 2012	Wang et al. 2000	
Johnsen et al. 2009	Xu et al. 2008	
Klein et al. 2020	Xu et al. 2014	**South Indian**
Koeser et al. 2020	Zhang et al. 2009	Curran et al. 2008

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Kribel and Ware 2014	Zhou et al. 2018	Metcalfe et al. 2008
Middleton 2009		
Negrón-Juárez et al. 2010		
Ogle et al. 2006		
Ostertag et al. 2005		
Oswalt and Oswalt 2008		
Pascarella 1997		
Prengaman et al. 2008		
Putz and Sharitz 1991		
Rivas-Cooper 1999		
Rodriguez-Robles et al. 1990		
Rutledge et al. 2021		
Sánchez Sánchez and Islebe 1999		
Van Bloem et al. 2005		
Vandecar et al. 2011		
Vandermeer et al. 1990		
Williams Linera et al. 2021		
Xi 2005		
Zimmerman et al. 1994		

Appendix Table A3. Tree species with High wind resistance ratings. Bolded species are our additions to the original Duryea et al. (2007a, b) rating lists. These new species come from hurricane studies that met our inclusion criteria (Appendix Table 1) and the ratings were assigned using our random forests model. Confidence indicates the probability a rating was correctly assigned according to the model. Asterisks (*) denote palm species from Duryea et al. (2007a, b). More detailed information for the species modeled in this study can be found at https://github.com/AllysonS/TreesForHurricanes.

Scientific Name	Confidence	Scientific Name	Confidence
*Adonidia merrillii**	na	*Kruglodendron ferreum*	na
Alstonia rostrata	**High**	***Jupunba macradenia***	**Moderate**
Alstonia scholaris	**Low**	*Lagerstroemia indica*	na
Amyris elemifera	**High**	***Larix kaempferi***	**Moderate**
Astronium graveolens	**Moderate**	*Latania toddigesii**	na
Bombax ceiba	**High**	*Livistona chinensis**	na
Bursera simaruba	na	***Luehea candida***	**Low**
*Butia capitata**	na	***Maclura tinctoria***	**Moderate**
Carya floridana	na	*Magnolia grandiflora*	na
Ceiba pentandra	**High**	***Manilkara hexandra***	**High**
Cenostigma gaumeri	**Low**	***Melicoccus bijugatus***	**Moderate**
*Coccothrinax argentata**	na	***Metasequoia glyptostroboides***	**Moderate**
Conocarpus erectus	na	***Myrsine seguinii***	**Moderate**
Chrysobalanus icaco	na	***Osmanthus fragrans***	**High**
Cordia sebestena	na	***Paraserianthes falcataria***	**Moderate**
Cornus florida	na	*Phoenix canariensis**	na
Dendropanax arboreus	**Low**	*Phoenix dactylifera**	na
Diospyros ferrea	**Low**	*Phoenix reclinata**	na
Dodonaea viscosa	**Moderate**	*Phoenix roebelenii**	na
*Dypsis lutescens**	na	***Photinia glabra***	**High**
Elaeocarpus angustifolius	**High**	*Podocarpus spp.*	na
Eugenia axillaris	na	*Ptychosperma elegans**	na
Eugenia confuse	na	*Quercus geminata*	na
Eugenia foetida	na	***Quercus incana***	**Moderate**
Eugenia reinwardtiana	**Low**	*Quercus laevis*	na

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Scientific Name	Confidence	Scientific Name	Confidence
Exostema caribaeum	**Low**	***Quercus margarettae***	**High**
Ficus macrophylla	**Moderate**	*Quercus myrtifolia*	na
Ficus racemose	**High**	*Quercus virginiana*	na
Fraxinus griffithii	**High**	*Sabal palmetto**	na
Geniostoma rupestre	**Low**	***Senna atomaria***	**Low**
Guaiacum officinale	**Low**	***Simarouba amara***	**Moderate**
Guaiacum sanctum	na	*Taxodium distichum*	na
Guazuma ulmifolia	**Moderate**	*Taxodium ascendens*	na
Gymnanthes lucida	**High**	***Thouinia paucidentata***	**Low**
Heliocarpus donnellsmithii	**Moderate**	***Thouinia striata***	**Low**
*Hyophorbe lagenicaulis**	na	*Thrinax morrissii**	na
*Hyophorbe verschaffeltii**	na	*Thrinax radiata**	na
Ilex cassine	na	***Toxicodendron succedaneum***	**Moderate**
Ilex glabra	na	***Vochysia ferruginea***	**Moderate**
Ilex opaca	na	***Vochysia guatemalensis***	**Moderate**
Ilex vomitoria	na		

Appendix Table A4. Tree species with Medium High wind resistance ratings. Bolded species are our additions to the original Duryea et al. (2007a, b) rating lists. These new species come from hurricane studies that met our inclusion criteria (Appendix Table 1) and the ratings were assigned using our random forests model. Confidence indicates the probability a rating was correctly assigned according to the model. Asterisks (*) denote palm species from Duryea et al. (2007a, b). More detailed information for the species modeled in this study can be found at https://github.com/AllysonS/TreesForHurricanes.

Scientific Name	Confidence	Scientific Name	Confidence
Acacia crassicarpa	**Moderate**	*Liquidambar styraciflua*	na
Acer floridanum	na	*Litchi chinensis*	na
Acer palmatum	na	***Lithocarpus longipedicellatus***	**High**
Acer pictum	**Moderate**	*Lysiloma latisiliquum*	na
Albizia odoratissima	**Moderate**	*Magnolia x soulangiana*	na
Annona glabra	na	*Magnolia virginiana*	na
Aphananthe aspera	**Low**	***Myrcia schiedeana***	**Low**
Artocarpus altilis	**Moderate**	***Nageia nagi***	**Moderate**
Betula nigra	na	*Nyssa aquatica*	na
Bischofia javanica	**Low**	*Nyssa sylvatica*	na
Blastus cochinchinensis	**Moderate**	*Ostrya virginiana*	na
Calophyllum antillanum	na	***Pictetia aculeata***	**Low**
Calophyllum calaba	**Low**	***Pistacia chinensis***	**Moderate**
Camellia oleifera	**Moderate**	***Plectrocarpa arborea***	**Low**
Carpinus caroliniana	na	***Pleiogynium timoriense***	**Low**
Carya aquatica	**Low**	***Pometia pinnata***	**Low**
Carya glabra	na	***Pouteria reticulata***	**Moderate**
Carya tomentosa	na	*Prunus angustifolia*	na
*Caryota mitis**	na	***Quercus hemisphaerica***	**Low**
Casearia nitida	**Low**	*Quercus michauxii*	na
Casearia thamnia	**Low**	***Quercus myrsinifolia***	**Moderate**
Castanopsis fissa	**Moderate**	*Quercus shumardii*	na
Castanospermum australe	**Moderate**	*Quercus stellata*	na
Ceiba aesculifolia	**Low**	*Roystonea elata**	na
Cercis canadensis	na	***Sassafras albidum***	**High**
Celtis sinensis	**Low**	***Senna siamea***	**Moderate**

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Scientific Name	Confidence	Scientific Name	Confidence
Chionanthus virginicus	na	*Sideroxylon foetidissimum*	na
Chrysophyllum oliviforme	na	*Simarouba glauca*	na
Coccoloba diversifolia	na	*Swietenia mahagoni*	na
Coccoloba uvifera	na	***Symplocos lancifolia***	**Low**
*Cocos nucifera**	na	***Syzygium buxifolium***	**Low**
Diospyros virginiana	na	***Syzygium cumini***	**Moderate**
*Dypsis decaryl**	na	***Tabernaemontana arborea***	**Moderate**
Fraxinus americana	na	***Terminalia tetraphylla***	**Low**
Hirtella triandra	**Moderate**	***Trichilia trifolia***	**Low**
Inga coruscans	**Moderate**	*Ulmus alata*	na
Lannea coromandelica	**Moderate**		

Appendix Table A5. Tree species with Medium Low wind resistance ratings. Bolded species are our additions to the original Duryea et al. (2007a, b) rating lists. These new species come from hurricane studies that met our inclusion criteria (Appendix Table 1) and the ratings were assigned using our random forests model. Confidence indicates the probability a rating was correctly assigned according to the model. More detailed information for the species modeled in this study can be found at https://github.com/AllysonS/TreesForHurricanes.

Scientific Name	Confidence	Scientific Name	Confidence
Acacia mangium	**Moderate**	***Guarea guidonia***	**Moderate**
Acer negundo	na	***Juniperus chinensis***	**Moderate**
Acer rubrum	na	*Kigelia pinnata*	na
Acer saccharinum	na	***Lagerstroemia speciosa***	**High**
Acronychia acidula	**Low**	***Leucaena leucocephala***	**Moderate**
Aegle marmelos	**High**	***Ligustrum lucidum***	**High**
Anacardium occidentale	**Low**	***Lindera kwangtungensis***	**Moderate**
Averrhoa carambola	na	***Lithocarpus glaber***	**Moderate**
Azadirachta indica	**Moderate**	***Machilus thunbergii***	**Moderate**
Bauhinia blakeana	na	***Magnolia champaca***	**Moderate**
Betula platyphylla	**Moderate**	*Mangifera indica*	na
Brosimum alicastrum	**Low**	***Matayba domingensis***	**Low**
Brosimum utile	**Moderate**	***Melia azedarach***	**Low**
Bucidas buceras	na	***Meliosma angustifolia***	**High**
Callistemon spp.	na	***Miconia elata***	**Moderate**
Calophyllum inophyllum	**High**	***Morisonia flexuosa***	**Moderate**
Calophyllum neoebudicum	**Low**	*Morus rubra*	na
Carapa guianensis	**Moderate**	***Myrcia deflexa***	**Low**
Carya texana	**High**	*Myrica cerifera*	na
Casearia sylvestris	**Moderate**	***Myristica globosa***	**Low**
Cecropia peltata	**Moderate**	***Olea europaea***	**Moderate**
Cedrus deodara	**Moderate**	***Ormosia krugii***	**Low**
Celtis laevigata	na	*Persea borbonia*	na
Celtis occidentalis	na	***Pinus caribaea***	**High**
Cinnamomum camphora	na	***Pinus echinata***	**High**
Chimarrhis parviflora	**Moderate**	*Pinus elliottii*	na
Chukrasia tabularis	**High**	*Pinus palustris*	na
Cinnamomum bejolghota	**Moderate**	***Pinus serotina***	**Moderate**
Cinnamomum burmanni	**High**	*Pinus taeda*	na
Citrus japonica	**Moderate**	***Pinus thunbergii***	**High**
Citrus spp.	na	***Piscidia piscipula***	**Moderate**
Cleyera japonica	**High**	***Platanus x hispanica***	**High**

Scientific Name	Confidence	Scientific Name	Confidence
Coccoloba tuerckheimii	**Low**	_Platanus occidentalis_	na
Coccoloba uvifera	**Moderate**	**_Platycladus orientalis_**	**High**
Cochlospermum vitifolium	**Low**	**_Plumeria rubra_**	**Moderate**
Colubrina arborescens	**High**	**_Populus heterophylla_**	**Moderate**
Cryptocarya chinensis	**Moderate**	**_Pouteria campechiana_**	**Moderate**
Dacryodes excelsa	**High**	_Prunus serotina_	na
Damburneya coriacea	**High**	**_Psidium guajava_**	**Moderate**
Delonix regia	na	_Quecus alba_	na
Distylium racemosum	**Moderate**	_Quercus laurifolia_	na
Drypetes lateriflora	**Moderate**	**_Quercus lyrata_**	**High**
Enterolobium cyclocarpum	na	_Quercus phellos_	na
Eriobotrya japonica	na	**_Quercus rubra_**	**High**
Erythroxylum rotundifolium	**Low**	**_Quercus velutina_**	**High**
Eucalyptus cinerea	na	**_Rockinghamia angustifolia_**	**Low**
Eucalyptus tereticornis	**Moderate**	**_Salix nigra_**	**Moderate**
Eucalyptus urophylla	**Low**	_Salix x sepulcralis_	na
Fagus grandifolia	**High**	**_Sarcosperma laurinum_**	**Moderate**
Ficus aurea	na	**_Symplocos sumuntia_**	**High**
Ficus benghalensis	**High**	**_Syzygium jambos_**	**High**
Flacourtia rukam	**Moderate**	_Tabebuia heterophylla_	na
Fraxinus mandshurica	**Moderate**	**_Talipariti tiliaceum_**	**Low**
Fraxinus pennsylvanica	na	_Terminalia catappa_	na
Fraxinus profunda	**High**	**_Toona ciliata_**	**Moderate**
Garcinia madruno	**Moderate**	_Ulmus americana_	na
Ginkgo biloba	**Low**	**_Ulmus rubra_**	**Moderate**
Gironniera subaequalis	**Moderate**	**_Vachellia farnesiana_**	**Moderate**
Guarea glabra	**Moderate**		

Appendix Table A6. Tree species with Low wind resistance ratings. Bolded species are our additions to the original Duryea et al. (2007a, b) rating lists. These new species come from hurricane studies that met our inclusion criteria (Appendix Table 1) and the ratings were assigned using our random forests model. Confidence indicates the probability a rating was correctly assigned according to the model. Asterisks (*) denote palm species from Duryea et al. (2007a, b). More detailed information for the species modeled in this study can be found at https://github.com/AllysonS/TreesForHurricanes.

Scientific Name	Confidence	Scientific Name	Confidence
Acacia auriculiformis	**Moderate**	**_Laetia procera_**	**Moderate**
Adina cordifolia	**Low**	**_Lepisanthes tetraphylla_**	**Low**
Aglaia pinnata	**High**	**_Licania hypoleuca_**	**Moderate**
Albizia julibrissin	**High**	**_Lindackeria laurina_**	**Moderate**
Albizia procera	**High**	**_Liquidambar formosana_**	**Moderate**
Alchornea latifolia	**Low**	_Liriodendron tulipifera_	na
Aleurites moluccanus	**High**	**_Luehea alternifolia_**	**Low**
Andira inermis	**Moderate**	**_Magnolia obovata_**	**Moderate**
Apeiba membranacea	**Low**	**_Manilkara bidentata_**	**Low**
Araucaria cunninghamii	**High**	**_Manilkara zapota_**	**Low**
Araucaria heterophylla	na	**_Maranthes panamensis_**	**Low**
Barringtonia asiatica	**Moderate**	_Melaleuca quinquenervia_	na
Bridelia retusa	**Low**	**_Miconia tetrandra_**	**Low**
Brosimum guianense	**Moderate**	**_Micromelum minutum_**	**Low**
Brosimum lactescens	**Low**	**_Mitragyna parvifolia_**	**Low**
Byrsonima crispa	**Low**	**_Morinda citrifolia_**	**Low**

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Scientific Name	Confidence	Scientific Name	Confidence
Byrsonima spicata	**Low**	***Neea psychotrioides***	**Moderate**
Calophyllum brasiliense	**Moderate**	***Ocotea leucoxylon***	**Low**
Cananga odorata	**Moderate**	***Otoba novogranatensis***	**Low**
Carya illinoensis	na	***Oxydendrum arboreum***	**Moderate**
Casearia arborea	**Low**	***Pachira aquatica***	**Moderate**
Casearia commersoniana	**Moderate**	*Persea americana*	na
Cassia fistula	na	*Peltophorum pterocarpa*	na
Casuarina equisetifolia	na	***Picea abies***	**High**
Catalpa bignonioides	**Moderate**	*Pinus clausa*	na
Cespedesia spathulata	**Moderate**	*Pinus glabra*	na
Chorisia speciosa	na	*Pipturus argenteus*	Low
Cordia bicolor	**Low**	***Planera aquatica***	**Moderate**
Cordia gerascanthus	**Low**	***Populus x canadensis***	**Moderate**
Cordia sulcata	**Low**	***Populus deltoides***	**Moderate**
Crescentia cujete	**Moderate**	***Pourouma bicolor***	**Moderate**
Croton poecilanthus	**Low**	***Protium pittieri***	**Low**
x Cupressocyparis leylandii	na	***Protium stevensonii***	**Moderate**
Cupressus sempervirens	**High**	*Prunus caroliniana*	na
Dimocarpus longan	**High**	***Prunus jamasakura***	**Low**
Dipteryx oleifera	**Moderate**	***Pseudolmedia spuria***	**Low**
Dussia macroprophyllata	**Low**	***Psychotria asiatica***	**Moderate**
Erythrina variegata	**High**	***Pterocarpus indicus***	**Moderate**
Eucalyptus robusta	**Moderate**	***Pterocarpus officinalis***	**Moderate**
Eurya japonica	**Moderate**	*Pyrus calleryana*	na
Fagus crenata	**Moderate**	***Quassia amara***	**Moderate**
Ficus benjamina	na	***Quercus acutissima***	**Moderate**
Ficus concinna	**High**	***Quercus aliena***	**Moderate**
Ficus elastica	**Moderate**	*Quercus falcata*	na
Ficus microcarpa	**Low**	*Quercus laurifolia*	na
Ficus religiosa	**Low**	***Quercus gilva***	**Moderate**
Ficus virens	**High**	***Quercus glauca***	**Low**
Firmiana simplex	**Moderate**	*Quercus nigra*	na
Fraxinus caroliniana	**Moderate**	***Quercus serrata***	**Moderate**
Gliricidia sepium	**Moderate**	***Robinia pseudoacacia***	**Moderate**
Grevillea robusta	na	***Salix babylonica***	**Moderate**
Guarea bullata	**Low**	***Sapindus mukorossi***	**Moderate**
Guarea grandifolia	**Moderate**	***Sapium laurocerasus***	**Low**
Guarea kunthiana	**Moderate**	*Sapium sebiferum*	na
Guarea pterorhachis	**High**	***Schefflera morototoni***	**Low**
Gyrocarpus jatrophifolius	**Low**	***Schleichera oleosa***	**Low**
Handroanthus chrysanthus	**Moderate**	***Sloanea berteroana***	**Low**
Handroanthus impetiginosus	**Moderate**	*Spathodea campanulata*	na
Heptapleurum actinophyllum	**Moderate**	***Stereospermum colais***	**Moderate**
Heptapleurum heptaphyllum	**Moderate**	***Styphnolobium japonicum***	**High**
Hernandia didymantha	**Low**	***Swietenia macrophylla***	**Moderate**
Holoptelea integrifolia	**Low**	*Syagrus romanzoffiana**	na
Homalium racemosum	**Low**	***Symphonia globulifera***	**Moderate**
Hymenaea courbaril	**High**	*Tabebuia caraiba*	na
Ilex verticillata	**Moderate**	***Tamarindus indicus***	**Moderate**
Inga laurina	**Moderate**	***Tapirira guianensis***	**Moderate**

Scientific Name	Confidence	Scientific Name	Confidence
Inga pezizifera	**Moderate**	***Tectona grandis***	**Low**
Inga thibaudiana	**Moderate**	***Terminalia amazonia***	**Low**
Ipomoea wolcottiana	**Low**	*Ulmus parvifolia*	na
Jacaranda mimosifolia	na	*Washingtonia robusta*	na
Juniperus silicicola	na	***Xylopia sericophylla***	**Low**
Khaya senegalensis	**Moderate**	***Xylosma intermedia***	**Moderate**
Lacistema aggregatum	**Moderate**		

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