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Stand and tree characteristics influence damage severity after a catastrophic hurricane disturbance

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ABSTRACT

Catastrophic wind disturbances can greatly impact the economic and ecological values of working forests worldwide. For example, Hurricane Michael caused severe economic damage in 2018 to commercial loblolly (*Pinus taeda* L.) and slash (*Pinus elliotti* Engelm.) planted pine stands in the southeastern U.S. This project examined the relative importance of prior management activities, stand characteristics, and soil and terrain attributes in predicting stand damage from a catastrophic hurricane event. We assembled data from land managers in coastal Alabama, the Florida panhandle, and South Georgia, on percent loss of trees after Hurricane Michael in over 400 stands, along with stand management history, and stand characteristics. Digital elevation models were utilized to determine terrain and hydrological characteristics of the landscape including aspect, channel distance, elevation, LS factor (slope and length steepness factor), slope angle, slope position, terrain ruggedness index, topographic wetness index, and wind exposition index. Random forest models were used to determine the relative accuracy of windspeed, management history, stand characteristics, and soil and terrain attributes in predicting stand damage. From the variables evaluated, stand density (as described by trees per acre), and tree height (as described by the average height of dominant and co-dominant trees) were among the most influential characteristics in predicting damage severity along with windspeed and linear distance from the coast. Stands with dominant heights > 14 m, trees per acre < 600 (trees per hectare < 1,483), and within 50 km of the coast were the most likely to experience severe damage. Topographic wetness index was the most influential terrain characteristic, with sands in wetter soils more likely to experience more severe damage. Recently thinned stands were slightly more vulnerable to severe damage. Results from this study can be used to develop vulnerability profiles for commercial pine stands in the coastal plain region in the southern U.S. region.

1. Introduction

Natural disturbances are an integral component of many forested ecosystems worldwide influencing forest patterns and processes (Angelstam, 1998; Aszalós et al., 2022; Yamamoto et al., 1995). Abiotic disturbances can range from wildfires, windstorms, ice storms, drought, flooding to landslide events, and some are undergoing regime changes due to global climatic changes (Flannigan et al., 2000; Seidl et al., 2011). The southeastern U.S. coastal plain region is especially experiencing more intense hurricane or cyclone activity in the past decade under climatic changes (Bhatia et al., 2018; Review et al., 2021) which has caused severe damage to commercial planted pine stands. Hurricane damage is part of the natural disturbance regime for coastal plain forests, however repeated disturbances can contribute to greater impacts from pests and pathogens, as well as increasing costs for landowners associated with timber loss and reforestation efforts (Chapman et al., 2008; Gandhi et al., 2007; Marini et al., 2013; McNulty, 2002; Vogt et al., 2020), and increasing costs of timber passed along to consumers (Henderson et al., 2022). Frequent hurricane events can adversely affect the sustainable management of commercial forests. Managed commercial stands have differing challenges and vulnerabilities compared to naturally regenerated stands, including the tendency toward even-age classes and low tree species diversity, which can increase vulnerability to broad-scale damage compared to stands with a diversity of species and age classes (Everham & Brokaw, 1996; Mitchell, 2013). The response of naturally regenerated stands to wind disturbance

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cannot always be extrapolated to commercial stands, therefore studies which focus on how management of commercial stands interacts with damage, are necessary to facilitate risk management planning and implementation of risk mitigation measures.

The distribution and extent of damage during a hurricane event are affected by multiple variables including windspeed, terrain, soils, tree, and stand characteristics, and further by land use history. Hurricane force winds were typically sustained in a radius of 75 km from the storm center, and sites within this radius would invariably be more prone to severe damage than those more distant from the storm center (Zampieri et al., 2020). Terrain features like slope and aspect can sometimes be more strongly associated with hurricane wind damage than the measures of storm meteorology (Kupfer et al., 2008). Topography creates variations in surface hydrology, which by extension can influence rooting and tree stability (Fan et al., 2017). Substrate texture and bedrock depth affects tree stability, thereby affecting likelihood of damage during a wind event (Fortuin et al., 2022; Loope et al., 1994; Phillips et al., 2008). Root development and nutrient availability are affected by the soil's chemical and physical properties. Low soil pH, for instance, may be associated with wind damage vulnerability in forests due to poor nutrient availability (Mayer et al., 2005). Well drained soils allow for deeper rooting, and poor soil drainage can lead to shallow root development, affecting tree stability during wind events (Nicoll & Ray, 1996). Rooting strategy is also related to tree species, as different species are adapted to different types of soil, and may vary in their response to soil moisture (Rutledge et al., 2021; Wang & Xu, 2008).

Stand structure and composition, including characteristics such as age, dominant tree height, density, and tree species may likewise interact with windthrow damage vulnerability (Taylor et al., 2019). Crown closure can reduce wind drag in the canopy and denser stands may promote interlocking root systems which provide additional wind firmness (Scott & Mitchell, 2005). However managed stands are generally thinned by age 14, which promotes an open canopy and means that older stands also lack the density for interlocking root systems, both potentially leading to higher windthrow vulnerability. Likewise older planted stands would generally have taller trees, and taller slender trees tend to be more prone to breakage from windstorm events (Díaz-Yáñez et al., 2019), and damage often increases linearly with tree height (Foster & Boose, 1992). However, trees in high density stands tend to allocate more growth to the crown than the roots, which could increase windthrow vulnerability due to this "top heavy" biomass allocation (Mitchell, 2013). Pine species vary in their vulnerability to damage in hurricane events, with species common to the lower coastal plain region, such as slash pine (*Pinus elliottii* Engelmann), being generally more resistant to hurricane damage than species with broader ranges, such as loblolly pine (*Pinus tadea* L.) (Gresham et al., 1991; Johnsen et al., 2009). It is likely that many stand characteristics therefore interact, and a clear understanding of relative risk related to wind damage beyond windspeed alone, based on known vulnerabilities associated with stand and tree characteristics, can facilitate appropriate and timely risk management decisions (Mitchell, 2013).

The catastrophic Hurricane Michael made landfall on 10 October 2018 as a category 5 hurricane, the strongest hurricane on record to hit the U.S. since Hurricane Andrew in 1992. The hurricane primarily affected the Florida panhandle including areas in and around Panama City, Florida, but hurricane-force winds continued as the storm entered southern Georgia. Hurricane Michael caused an estimated 25 billion dollars in economic damage to the U.S. (Beven et al., 2019). Large tracts of commercial forest were affected by Hurricane Michael in the Florida panhandle, coastal Alabama and southern Georgia with > 2 million ha of forests in Florida and Georgia alone (Georgia Forestry Commission, 2018). Hurricane Michael provided an opportunity to examine the efficacy of different variables, including use history, in predicting damage severity to a catastrophic wind disturbance. Hence, our research objectives were to: 1) determine the relative influence of prior management, stand characteristics, soil characteristics, and terrain attributes in predicting the likelihood of severe stand damage; 2) determine which individual variables are most influential in predicting severe damage levels; and 3) determine if past management activity in working pine is influential in predicting stand damage level. We used data collected by land managers in Alabama, Florida panhandle, and southern Georgia before and after Hurricane Michael. Management data, stand characteristics, soil characteristics and terrain attributes were utilized as predictor variables, and lost timber volume per acre (VPA) was used to create two response categories: low damage (0 to 25 % VPA lost); and high damage (>40 % VPA lost). Note that 93 % of stands in the low damage category sustained 0 to 10 % loss, with only 7 % of stands in this category sustaining 20 to 25 % loss. Conversely 74 % of stands in the high damage category sustained >75 % loss. These two categories are therefore very representative of the extremes of low and high damage levels. We used a series of predictive models using the well documented random forest algorithm, to determine the relative accuracy of management data, stand characteristics, soil characteristics, and terrain attributes in predicting damage level compared to windspeed alone, and determine the variables which were most influential in predicting damage. Given the multitude of variables which have the potential to contribute to wind damage, an examination and selection of the most influential variables, and their interactions, can facilitate both risk management decisions and future risk model development in working forests. The purpose of this study thus was to identify relevant variables for risk management focus, specific to planted commercial stands especially in the coastal plain.

2. Methods

2.1. Data collection and preparation

Data were collected from a total of 423 stands from a total of 16,744 ha in the Florida panhandle, southern Alabama, and southern Georgia. All stands were in the path of Hurricane Michael, a category 4–5 hurricane which made landfall in October 2018. All stands were owned by Timber Investment Management Organizations (TIMO's). Post damage assessments were estimated by the landowners based on lost timber volume per acre (VPA). For each stand, the landowners provided the most recent stand metrics before the storm in 2018, as well as management history and soil taxonomic type for each stand. Most stand metrics were from 2016 (32 %) or 2017 (47 %), 7 % were from 2018 before the storm, 10 % were from 2015, with the remaining 4 % taken between 2012 and 2014. Average stand size was 97 acres (39 ha), with a median of 68 acres (27 ha) and ranged from < 1 to 682 acres (<0.4 to 275 ha).

The average sustained windspeeds from hurricane Michael were downloaded from the NOAA best tracks database and mapped via the HURRECON model in R (Boose et al., 2001) to extract average windspeeds sustained by each stand. Euclidian distance from the coast, calculated for each 1 km^2 pixel within the study area, was used and averaged across each stand polygon. Stand variables describing each pine stand included pre-hurricane basal area (ft^2 per acre), stand density (TPA), site index base age 25, average height of the dominant and co-dominant trees (dominant height), primary tree species (loblolly pine or slash pine), and site type (bottom land, ridge, wet flat, and coastal flat).

Data on soil pH, permeability, drainage class, and soil texture of surface (A-layer) and sub soil layers (B and C layers) for each soil taxonomic group were obtained from the United States Department of Agriculture (USDA) National Cooperative Soil Survey, Official Soil Series Description (United States Department of Agriculture, 2021). Drainage class categories were designated as a ranked numeric variable 1 – 7 as follows based on the USDA soil survey: "Very poorly drained", "Poorly drained", "Somewhat poorly drained", "Moderately well drained", "Well drained", "Somewhat excessively drained", or "Excessively drained". Soil permeability was designated as a ranked numeric

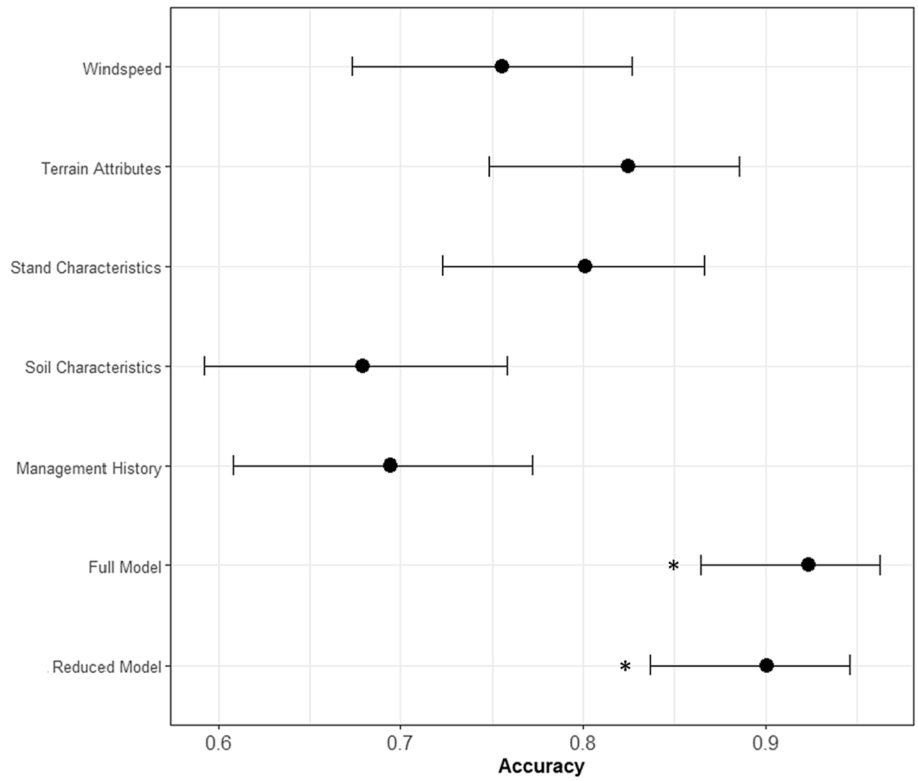

Fig. 1. Comparison of the accuracy of different random forest models in predicting lost percent volume per acre (VPA) in pine stands after Hurricane Michael. Lines represent 95% confidence intervals. Stars indicate significant difference in accuracy of the model prediction relative to the windspeed only model. The reduced model included the following variables: windspeed, distance to coast, dominant height, and stand density (TPA).

variable 1 – 7 as follows: "Very slowly permeable", "Slowly permeable", "Moderately slowly permeable", "Moderately permeable", "Moderately rapid permeable", "Rapidly permeable", or "Very rapidly permeable". Soil acidity was ranked 1–5 as "Neutral", "Moderately acidic", "Strongly acidic", "Very strongly acidic", or "Extremely acidic". Terrain attributes were derived from the Shuttle Radar Topography Mission (SRTM) 30 Arc-Second elevation map, using SAGA GIS terrain modules. The attributes include aspect, channel distance, elevation, LS factor (slope and length steepness factor), slope angle, slope position, terrain ruggedness index, topographic wetness index, and wind exposition index. Data on prior management included dates of fertilizer, herbicide, and thinning treatments, and whether stands were bedded. Fertilizer, herbicide, and bedding treatments were considered as binomial variables, with each stand having either received the treatment during the silvicultural rotation period when the hurricane made landfall (1) or not having received the treatment during the cycle (0). Thinning treatments were treated as categorical considering the amount of time since thinning treatment at the time the hurricane made landfall: $<$ 5 years prior, 5–10 years prior, $>$10 years prior, or unthinned. A total of 28 predictor variables were included in the study (S1).

2.2. Data analyses

Random forest has been shown to accurately predict wind damage to individual trees using stand, soil, and tree characteristics, and have outperformed other machine learning techniques in classifying tree damage for data sets with missing input variables (Hart et al., 2019). Random forest was selected due to its ability to handle missing data and mixed-type data (categorical, ranked, and continuous variables), in addition to the capability of returning measures of variable importance (Cutler et al., 2012; Genuer et al., 2010), and minimization of overfitting (Breiman, 2001). Random forest was used to examine the relative accuracy of different groups of variables in predicting level of damage from the hurricane. Random forest is a non-parametric machine learning classification algorithm which does not require assumptions about the distribution of the data, nor a parametric model. A random forest is an assemblage of un-pruned decision trees created from a random selection of samples, with replacement, in a training data set. The most common vote associated with all the decision trees in the random forest generates the overall prediction, after which the unused samples ("out of bag" or OOB samples) are used to test the goodness of fit of the predictions (Ali et al., 2012; Catani et al., 2013). Random forests minimize overfitting via the use of multiple decision trees and the majority vote process for making predictions (Breiman, 2001).

To maximize the number of complete cases for data analysis, a random forest imputation utilizing the R package missForest (Stekhoven & Bühlmann, 2012) was used to fill in missing data in the original data set. The data set of 423 stand contained 230 complete cases (stands for which all 28 predictor variable measurements were available), and 193 stands missing a measurement for at least one of the 28 predictor variables under consideration. Random forest imputation utilizes an iterative process of training and predicting the missing values utilizing the observed values. Out of bag (OOB) normalized root mean squared errors (NRMSE) are then computed for continuous variables and proportion of falsely classified (PFC) is computed for the categorical variables in the imputed data set (Cutler et al., 2012). Random forest imputation has been shown to be highly robust for datasets with moderate to high levels of missingness (Tang & Ishwaran, 2017). The response variable for all models was level of damage, based on lost timber volume per acre (VPA), and was classified into three categories: low damage (0 – 25 % lost volume, $n = 225$) or high damage ($>$40 % lost volume, $n = 198$). These categories allow for similar class sizes to facilitate the random forest analyses.

For random forest models, 70 % of the data were used for training and 30 % for testing. This was done for each category of variables separately: management history, soil characteristics, stand

Table 1
Random Forest model comparisons, including out of bag (OOB) error, accuracy (Acc) and 95% confidence interval of Acc for each model in predicting lost percent volume per acre (VPA) in pine stands after Hurricane Michael. *P*-value is the significance of the model results being greater than the No Information Rate (NIR) of 0.5544, or the rate that would be expected at random. The reduced model included the following variables: windspeed, distance to coast, dominant height, and stand density (TPA).

Model	OOB error	Acc	95 % CI	*P*-Value [Acc > NIR (0.5344)]
Full model - all variables	11.30 %	0.9237	(0.8641, 0.9628)	<0.001
Reduced model	11.30 %	0.9008	(0.8363, 0.9461)	<0.001
Terrain attributes	18.15 %	0.8768	(0.8101, 0.9266)	<0.001
Windspeed	24.66 %	0.7557	(0.673, 0.8265)	<0.001
Stand characteristics	25.34 %	0.7541	(0.7229, 0.8661)	<0.001
Management history	24.66 %	0.6947	(0.6082, 0.7721)	<0.001
Soil characteristics	28.08 %	0.6794	(0.5923, 0.7582)	<0.001

characteristics, terrain attributes, and windspeed. A full model was then generated containing all variables. The number of classification trees was selected for each random forest using visual inspection of error rate curves to determine the number of trees at which error rates plateau, starting with 1,000 classification trees in the initial model. The number of nodes selected for splitting classification trees was determined by comparing OOB errors across a series of models with different node values based on the number of predictor variables in the model, from Y_1 to Y_n, using the number of trees determined in step 1. The number of nodes which produced the lowest OOB error was selected. The caret package (Kuhn, 2022) was used to test model accuracy, and determine if the accuracy (Acc) was statistically significant when compared to the no information rate (NIR) (the rate equal to the largest proportion of observed damage classes). The NIR represents the percentage of the most common level of damage, thus an accuracy that is significantly different from the NIR indicates that the model can predict damage better than at random. Each model was compared pairwise to the location model using McNemar's Chi-squared test with continuity correction, to determine which groups of variables predicted damage significantly better or worse than location alone. The influence of individual variables on the probability of damage from the full model was examined using partial dependence plots for the five most influential variables and management history variables, utilizing the "pdp" package in R (Greenwell, 2017). Interactions between the most influential variables and windspeed were examined with two-way partial dependence plots. A backwards elimination process was then applied to reduce the full model. Starting with variables which had a mean decrease in in accuracy score of at least 10 (i.e., the mean number of cases misclassified if the variable was absent from the model was at least 10), each variable was eliminated sequentially and Acc values checked at each step to determine the minimum number of variables that could be considered without compromising overall model accuracy. Selected variables were additionally checked using the VSURF package in R (Genuer et al., 2015).

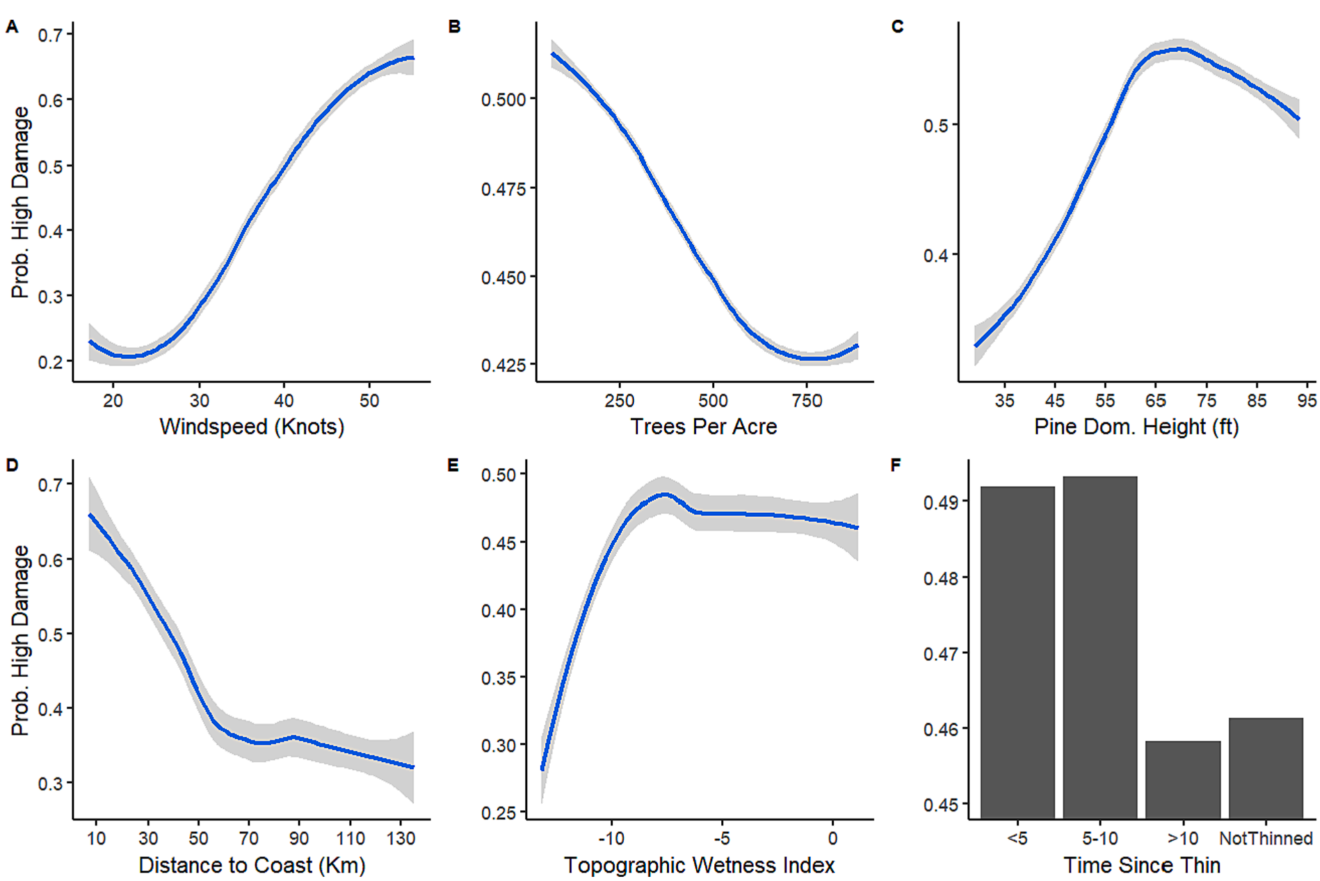

Fig. 2. Partial dependents plots of important predictor variables of Hurricane Michael damage: A) linear distance to the coast (Km), B) pine dominant height (ft.), C) topographic wetness index (dimensionless index of soil wetness), D) stand density as measured by Trees per Acre, E) Windspeed, and F) time since the last thinning of the stand. Y axis represents the relative contribution of the variables on the probability of the highest pine stand damage level (>40 % lost volume per acre).

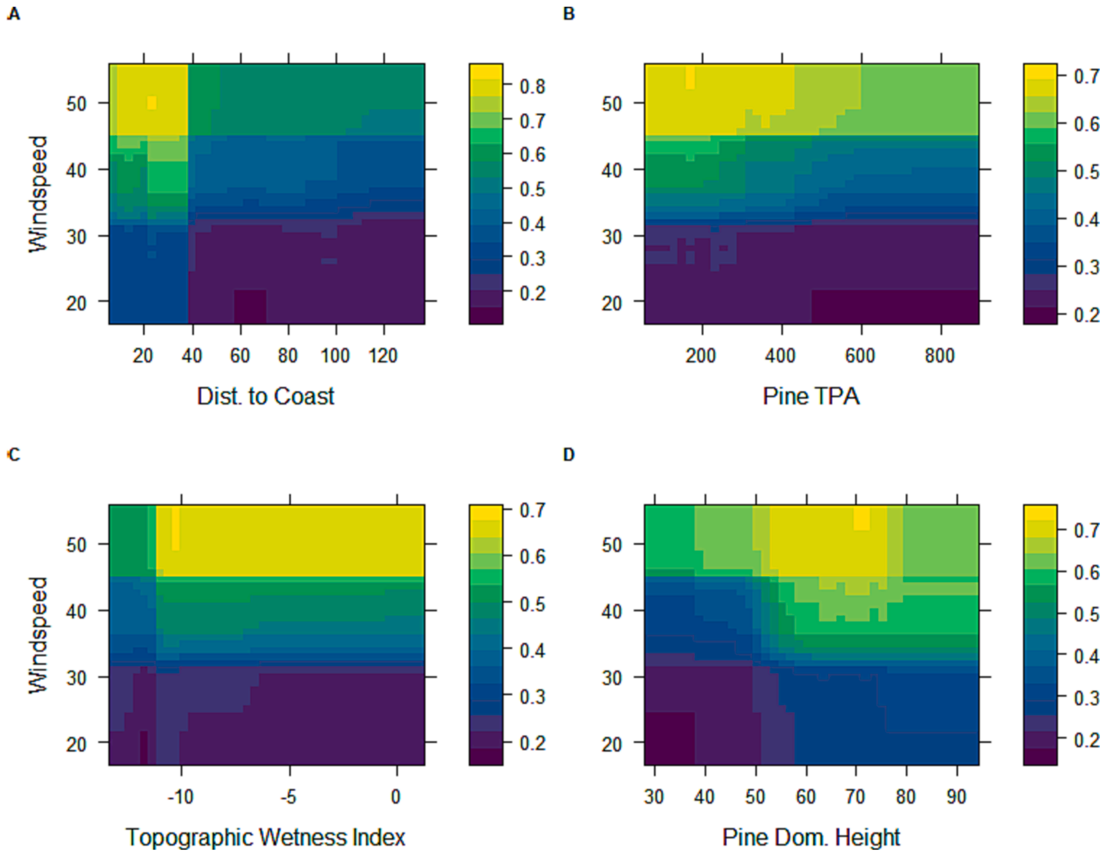

Fig. 3. Two-way partial dependence plots for windspeed interactions with other variables in predicting lost percent volume per acre (VPA) in pine stands after Hurricane Michael: (A), Linear distance to the coast (km) (B), Stand density as measured by pine trees per acre (TPA), (C) Topographic wetness index, a measure of soil moisture (D) Pine Dominant Height (ft). Color bar represents the relative contribution of the variables on the probability of the highest pine stand damage level (>40 % lost volume per acre).

3. Results

Out of bag (OOB) normalized root mean squared error (NRMSE) for the continuous variables in the imputed data was 0.07, and OOB proportion of falsely classified entries (PFC) in the categorical variables of the imputed data was 0.01. Given the low error rates, imputed data was used for all models. All random forest models, including management history, soil characteristics, stand characteristics, terrain attributes, windspeed, the full model containing all variables, and the final reduced model had > 67 % accuracy in predicting damage, and all were significant compared to the no information rate (NIR) of 53.44 % (*P*-Value [Acc > NIR]: < 0.001) (Fig. 1). The model containing only windspeed had an accuracy (Acc) of 75.57 % in predicting damage level when applied to the test set (Table 1). Soil characteristics alone (i.e., drainage class, soil texture, etc.) had an Acc of 67.94 %. Management history alone (i.e., thinning history, fertilizer treatment, etc.) had an Acc of 69.47 %. Terrain attributes (i.e., elevation, slope, etc.) predicted damage with an Acc of 87.68 %. Stand characteristics alone (i.e., primary tree species, TPA, dominant height, etc.) had an Acc of 75.41 %. The full model which included all variables (windspeed, management history, stand characteristics, soil characteristics, and terrain attributes) had the highest accuracy in classifying damage level, with an Acc of 92.37 %.

Backward elimination reduced the full model to four variables in the following order of importance: windspeed, distance to coast, dominant height, and stand density, with an accuracy of 90.08 %. The full model and reduced model both predicted damage significantly better than windspeed alone, the other models were not significantly better at predicting damage than windspeed alone (Fig. 1). The probability of damage increased linearly starting at windspeeds above 30 Knots (Fig. 2A). Lower density stands (TPA <600), stands with taller trees [dominant height > 45 ft. (>14 m)], and within 50 km of the coast were most prone to high damage levels (Fig. 2 B-D). Topographic wetness index was among the top terrain variables, with an increasing risk of damage in wetter areas (Fig. 2E). Time since last thin was the most important management variable, with stands that had been thinned within the past 10 years prior to the storm experiencing higher damage (Fig. 2F).

The effects of windspeed are not constant across all levels of the other main predictor variables. Stands closer to the coast show higher probability of damage at all windspeed levels (Fig. 3A), and a similar pattern is observed relative to stand density, with lower density stands showing higher damage across all windspeed levels (Fig. 3B). The effect of windspeed is constant across all topographic wetness (TWI) levels, with risk increasing unilaterally across all windspeeds once TWI reaches a value of −7 (Fig. 3C). Stands with dominant heights between 50 and 75 feet (15 to 23 m) had increased damage vulnerability at the highest windspeeds (Fig. 3D).

Stands with lower density (< 400 TPA) were most vulnerable within 40 km of the coast (Fig. 4A). Stand density showed interaction with topographic wetness, as lower density stands had higher vulnerability in wetter areas compared to higher density stands (Fig. 4B). There was an interaction between stand density and dominant tree height whereby in lower density stands, dominant heights between 65 and 75 feet (20–22 m), had a higher risk of damage, while in high density stands dominant tree height has a less pronounced effect, and vulnerability to damage is lower overall (Fig. 4C). Management history variables did not contribute substantially to overall model accuracy, and none were included in the reduced model, however thinning history showed a pattern of

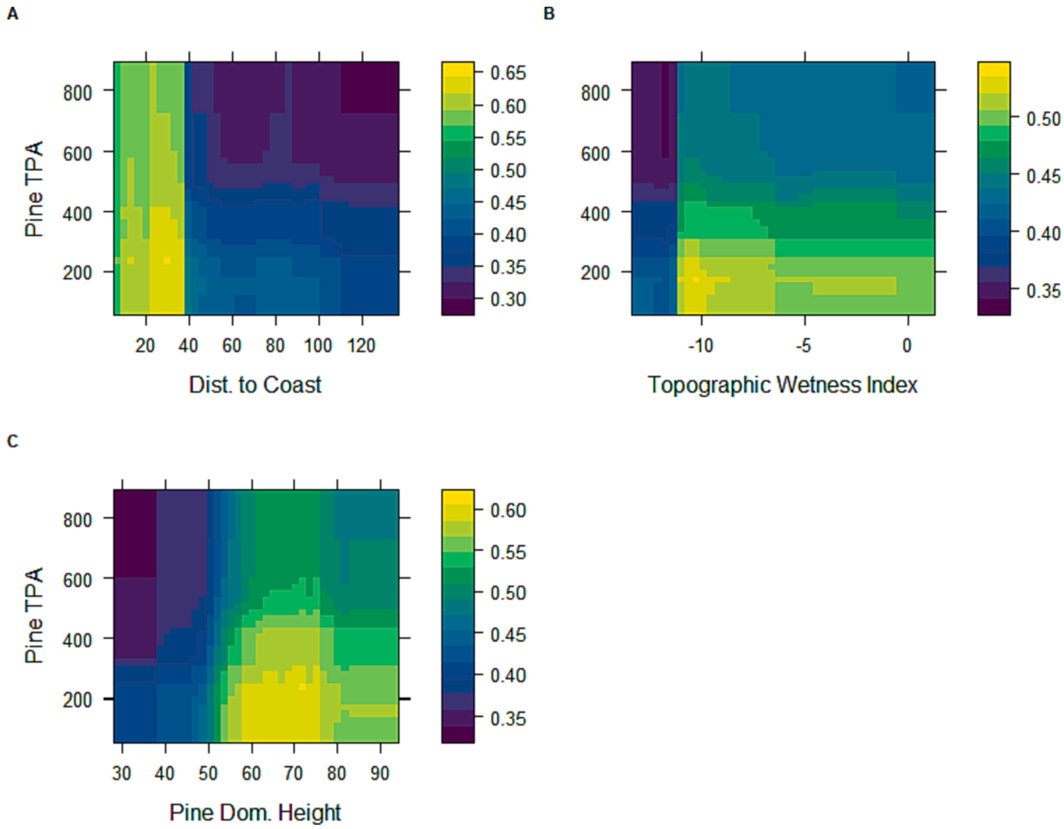

Fig. 4. Two-way partial dependence plots for stand density as measured by pine trees per acre (TPA) interaction with other variables in predicting lost percent volume per acre (VPA) in pine stands after Hurricane Michael: (A), Linear distance to the coast (km) (B), Topographic wetness index, a measure of soil moisture (C) Pine Dominant Height (ft). Color bar represents the relative contribution of the variables on the probability of the highest pine stand damage level (>40 % lost volume per acre).

decreasing damage probability relative to the time since the last thin, with stands thinned within the last ten years having slightly higher vulnerability (Fig. 2F).

4. Discussion and management implications

Our study confirms that stand characteristics including stand density and dominant tree height were among the most important variables for predicting forest stand damage from a catastrophic hurricane in the coastal plain. Other groups of variables including soil characteristics and management history were less influential for predicting damage but make small relative contributions to damage vulnerability. Stands within 50 km of the coast, dominant height > 45 ft (>14 m), and TPA < 600 (trees per hectare < 1,483), were the more likely to experience the highest levels of damage from this catastrophic wind disturbance event.

Our study indicated that stand density interacted with multiple variables including dominant height and topographic wetness index, with lower density stands having the highest vulnerability overall, especially with taller trees and wetter soils. A similar study which looked at forest damage after Hurricane Ivan in 2004 in coastal Alabama and the Florida panhandle, found in contrast that stands with higher basal area and denser planting to be more vulnerable to windthrow (Sharma et al., 2021). However, other studies in various systems have found conflicting results relative to stand density and windthrow vulnerability (Mitchell, 2013; Polinko et al., 2022; Rutledge et al., 2021; Wang & Xu, 2008), suggesting stand density interacts with other variables. As one might predict, stands closer to the coast were more severely damaged, with all stands showing the strongest response to coastal proximity at threshold at 50 km Euclidean distance from the coast. Hurricane Michael was a particularly high intensity storm, it is possible that lower intensity storms may have a different distance threshold.

Other studies have indicated that terrain variables can be very important predictors for wind damage events in forests (Fortuin et al., 2022; Kupfer et al., 2008), but when stand characteristics are considered, they often are more important than terrain (Taylor et al., 2019). The model containing only terrain variables in our study had more predictive value than windspeed alone, however the most important terrain variable in the full model was topographic wetness index, which is calculated as:

$\ln(a/\tan(b))$.

Where a is the upslope drainage area to a central pixel with respect to the pixel length and b is the slope of the central pixel in radians. This measure is an indicator of runoff flow direction and water accumulation and can be considered a proxy for soil moisture, where negative numbers represent lower soil moisture, positive number indicate higher soil moisture (Böhner & McCloy, 2006; Kopecký et al., 2021). This finding concurs with our previous work showing soil wetness increases vulnerability of windthrow damage from tornado and severe thunderstorm events, specifically for pines (Fortuin et al. 2021). However topographic wetness was not included in the final reduced model, nor were any other terrain attributes. The reason for this may be due to the geographic range of the current study, which was limited to the lower coastal plain of the coastal Alabama, Florida panhandle, and South Georgia. The landscape in this area largely consists of flat, low-elevation areas with minimal slopes or ruggedness. For example, elevation in the region under study only ranged from 11 to 107 m, with all slopes < 20°. Since the southeastern U.S. coastal plain region is largely homogeneous in its terrain, the current model may not be as relevant in coastal areas with greater ranges of elevation and steeper slopes. Likewise, soils in the region of this study were largely sandy loam/loamy sand, acidic soils.

Clay soils and more alkaline soils were not well represented in this area. Similarly, analyses of a broader area with more variation in soil texture and acidity might reveal differences which were not significant in the current study.

An objective of this study was to determine management strategies which could mitigate damage risk. While there were patterns noted related to timing of thinning, the effects on damage level were not strong enough to recommend any specific practices in coastal plain forests. Risk mitigation strategies instead may consider higher density planting when practical in areas that are within 50 km of the coast, especially in wetter areas, to reduce economic impacts.

Overall, this study provided important information related to how various tree, stand, and geographical attributes may have contributed to levels of tree mortality during the catastrophic Hurricane Michael. As global climate changes, the Atlantic and Gulf Hurricanes are expected to become more intense with much higher economic impacts including loss of timber, and subsequent salvaging and reforestation efforts (Peterson, 2000). These damaged and stressed forest stands may also become more vulnerable to pests and pathogens including pine bark beetles (Vogt et al., 2020). Drought conditions could also exacerbate sensitivity to wind damage (Bigelow et al., 2021). Hence, long-term sustainability of pine forests will be dependent on adapting to these climatic changes through silvicultural manipulations that will vary as based on site conditions (Bigelow et al., 2021). For example, tree density and when to harvest may be different in areas closer to the coast than further away, thus creating a mosaic of landscape-level features across planted pine stands. This may bypass the uncertainty related to the probability of when, where, and how intense hurricane may occur in each area. While landscape-level considerations have rarely been incorporated in management plans, they may become a necessity due to climate changes and included as a part of risk management strategies in the southeastern U.S. (Stanturf et al., 2007), and other forested areas that are more prone to catastrophic wind disturbances.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foreco.2023.120844.

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