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RESEARCH ARTICLE

Predicting risks of tornado and severe thunderstorm damage to southeastern U.S. forests

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Abstract
Context The southeastern U.S. experiences tornadoes and severe thunderstorms that can economic and ecological damages to forest stands resulting in loss of timber, reduction in short-term carbon sequestration, and increased susceptibility to forest pests and pathogens.
Objectives This project sought to determine landscape-scale patterns of recurring wind damages and their relationships to topographic attributes, overall climatic patterns and soil characteristics in southeastern forests.
Methods We assembled post-damage assessment data collected since 2012 by the National Oceanic and Atmospheric Administration (NOAA). We utilized a regularized Generalized Additive Model (GAM) framework to identify and select influencing topographic, soil and climate variables and to discriminate between damage levels (broken branches, uprooting, or trunk breakage). Further, we applied a multinomial GAM utilizing the identified variables to generate predictions and interpolated the results to create predictive maps for tree damage.
Results Terrain characteristics of slope and valley depth, soil characteristics including erodibility factor and bedrock depth, and climatic variables including temperatures and precipitation levels contributed to damage severity for pine trees. In contrast, valley depth and soil pH, along with climactic variables of isothermality and temperature contributed to damage severity for hardwood trees. Areas in the mid-south from Mississippi to Alabama, and portions of central Arkansas and Oklahoma showed increased probabilities of more severe levels of tree damage.
Conclusions Our project identified important soil and climatic predictors of tree damage levels, and areas in the southeastern U.S. that are at greater risk of severe wind damage, with management implications under continuing climate change.

Keywords Forests · Predictive models · Tornadoes · Tree damage · Windthrow

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Introduction

The southeastern U.S. represents America's "wood basket", producing 60% of the total timber volume of the U.S., and representing 80 million ha of private forest land and 13 million ha of public forest land (Butler and Wear 2013; Oswalt and Smith 2014). This region is subject to significant and increasing tornado activity (Dixon et al. 2011; Ashley and Strader 2016), and exposure to both Atlantic and Gulf hurricanes. While these wind events are part of natural disturbance in southeastern forests, they can cause substantive economic and ecological damage to forest stands resulting in the loss of timber, increased reforestation efforts and costs, reduction in carbon sequestration, rapid expansion of invasive plant populations, and a potential increase in forest pest and pathogen populations (McNulty 2002; Gandhi et al. 2007; Chapman et al. 2008; Marini et al. 2013; Vogt et al. 2020). Recovery periods for damaged forest stands to reach structural similarity to undamaged forest stands can take up to 25 years in U.S. temperate forests (Allen et al. 2012). Frequent wind events have major impacts on forest resilience and economic sustainability in commercial forests, and therefore, understanding patterns of events and risks associated with damage from wind events is critical for risk management and planning.

A severe thunderstorm is defined by the National Oceanic and Atmospheric Administration (NOAA) as any storm which produces at least one of the following: hail of one-inch diameter or greater, wind gusts exceeding 50 knots (93 km/h), or a tornado (Kupfer et al. 2008; National Oceanic & Atmospheric Administration 2018). Severe thunderstorms can cause significant wind damage to forests alone through straight line winds and strong gusts, and can produce damage that is very similar to tornado damage, however tornados tend to cause more severe damage. Tornadoes can produce 3-s wind gusts from 56 knots (104 km/h) for EF0 tornadoes and upwards of 175 knots (324 km/h) in EF5 tornadoes (National Oceanic & Atmospheric Administration 2018). Tornado events vary widely in path length and width. The mean path length for weaker (F0) tornadoes is 1.4 km, and path length tends to increase along the F scale to over 50 km for the strongest (F5) tornadoes. Mean width also varies widely from < 30 m for F0 tornadoes and a wide as 550 m for the strongest tornadoes (Brooks 2004). Adding to the complexity of tornadoes is the variation in airflow, direction, and speed within an individual tornado vortex and throughout the larger storm cell. The erratic nature of tornado events is reflected in damage patterns on the ground, which is often patchy in nature (Cannon et al. 2016). This can be juxtaposed to damage patterns created by sustained wind events such as a hurricane, where broader areas may be affected (Wang and Xu 2009). Damage associated with long-duration wind events is often predicted by tree characteristics including species, age, diameter, height, crown size, planting density, and crown density often explain damage variation at the local scale (Peterson 2000b; Xi et al. 2008; Johnsen et al. 2009; Kamimura et al. 2019; Rutledge et al. 2021; Sharma et al. 2021). For example, mechanistic models have shown that irregular spaced stands tend to experience scattered damage, where regular stands can be resilient to lower wind speeds and experienced collapse above a critical wind speed (Ancelin et al. 2004). For tornadoes, damage patterns (i.e., the distribution of damage within the storm path) and damage severity (i.e., total area affected or damage magnitude) may vary with the topographic configuration of the landscape. Surface topography affects tornado direction and intensity, with even small changes influencing near-surface inflow, structure, and path (Lewellen 2012). Steeper slopes have been shown to increase probability of tornado occurrence, likely due to the role of slope in the creation of updraft, although the relationship between elevation and tornadic activity can vary by region and storm characteristics (Frazier et al. 2019; Houser et al. 2020). Remote sensing studies after tornado damage in Georgia and Tennessee forests found more severe damage as tornados descended ridges and diminished damage on the ascent, and this pattern was more pronounced on shallower than steeper slopes (Cannon et al. 2016). Numeric simulations suggest surface roughness and topography can influence the near surface swirl of tornados, thus modifying the intensity at ground level (Lewellen 2012). Further, terrain features like slope and aspect can sometimes be more strongly associated with damage than the measures of storm meteorology during hurricane events (Kupfer et al. 2008).

Soils represent another important consideration for tree and stand vulnerability, as substrate conditions, soil moisture, and depth of bedrock can affect tree stability during wind events (Loope et al. 1994; Phillips et al. 2008). Poor soil drainage can lead to shallow root development, potentially increasing risk of windfall, however shallow root systems can also equal a larger proportion of biomass allocated to roots, as well as increased root contact between trees, both of which can increase stability from windthrow (Nicoll and Ray 1996). Different tree species have adaptations for rooting into different types of soil (Wang and Xu 2009). Hence, soils and drainage class can interact with species vulnerability, for example oak (*Quercus* spp.) trees are more vulnerable to damage in drier soils while pine (*Pinus* spp.) trees have increased resistance to wind damage in drier soils (Rutledge et al. 2021). Chemical and physical properties of the soil can affect root development and nutrient availability, which in turn influences tree health and root stability. For example, low soil pH can be related to wind damage vulnerability in forests, possibly due to lower nutrient availability in these soils (Mayer et al. 2005).

Vulnerability at the stand and individual tree scales is one facet of an overall understanding of risk, but can be limited in terms of broader spatial application (Kupfer et al. 2008). Risk takes into account likelihood of an event along with expected damage magnitude (Hanewinkel et al. 2011). This estimation can be accomplished through integration of probability models with spatial data, which can provide high-resolution disturbance risk information over broad geographic areas (Suvanto et al. 2019). Landscape-scale patterns of damage and the relationships of those patterns to topography and soils are needed to fill gaps in our understanding of wind disturbance in southeastern forests (Peterson et al. 2016). Understanding these patterns of periodic wind disturbances can allow forest systems to be managed prior to disturbances in ways that alter how the system would respond based on its particular vulnerabilities (Kupfer et al. 2008). In this way, management for wind damage can take place within a larger context of risk management, and by integrating understanding of likelihood and severity into the broader aims of stand management practices (Mitchell 2013).

Our research objectives were to: (1) determine the landscape-scale patterns of event probability and damage across the region; (2) determine the topographic, climactic and soil variables which separate the probabilities of different damage classes at the landscape scale; and (3) develop predictive models of wind damage severity in forests over the southeastern U.S. We used post-damage assessments conducted during 2012–2020 across the southeastern region by the National Oceanic and Atmospheric Administration (NOAA). Topographic, soil and climate data were utilized as predictor variables, and event probability was integrated to develop risk maps. This information can be integrated with on-the-ground vulnerability analyses based on species and stand structure characteristics at the local scale for a more complete understanding of risk for the individual landowner. For the purposes of this paper, we focused our attention on tornados and severe thunderstorms because of the availability of NOAA's post-damage assessment data, which allowed for a regional scale analysis of damage risk related to these specific events. However similar predictive modelling processes could be applied to hurricanes and other wind events if region-wide post-event damage data were readily available.

Methods

Data collection and preparation

To develop a regional scale spatial context of probability and magnitude, wind event history data were obtained from the NOAA, National Weather Service (NWS) Storm Prediction Center (National Oceanic and Atmospheric Administration 2020, https://www.spc.noaa.gov/gis/svrgis/). Tornado path data for 1950–2019 includes start and end points, width of track (measured as the mean damage path width), magnitude on the F scale before 2007, and the EF scale after 2007. The tornado path data is collected by NOAA from National Weather Service's field offices and reviewed by the National Climate Data center and Storm Prediction Center. Data are generally collected via on-the-ground damage surveys, and satellite or remote sensing tools are sometimes used in leu of or in combination with ground surveys (National Oceanic & Atmospheric Administration 2018). The data on tornado incidents included line shapefiles for tornado events across the Southeastern U.S. The line shapefile data were rasterized to 1 km^2 resolution using R statistical software package "raster" (Hijmans and Etten 2012). Rasterization was accomplished by calculating the total number of linear tracks traversing each 1 km^2 pixel. Probability of tornadoes within each km^2pixel were then calculated based on numbers of linear tracks divided by the number of years of data. Average magnitude per pixel was calculated based on the minimum 3-s gust associated with the EF scale for all tornados traversing the km^2 area from 2007 onwards. The minimum 3-s gust associated with severe thunderstorm damage is 93 km/h. The minimum 3 s gusts for EF 0—EF 5 tornadoes are 105, 138, 179, 219, 267, and over 322 km/h, respectively (McDonald and Mehta 2004). Magnitude was only considered for 2007 onwards due to the change in magnitude scale applied in 2007 by NOAA from the F to EF scale. The 1 km^2 resolution was used for all analysis, but for visualization, maps for tornado probability and average magnitude were interpolated using bilinear interpolation, then aggregated and smoothed with a focal operation with a factor of 10.

Tree damage data for the southeastern U.S. was gathered from NOAA post-damage assessments, obtained via the damage assessment viewer website (https://apps.dat.noaa.gov/StormDamage/DamageViewer/) for 2012–2020. Post-damage assessments were conducted by field personnel after a damaging tornado or storm, to assess damage to buildings, trees, and other structures. This damage information is utilized by NOAA to categorize the tornado based on the EF scale. Only tree damage was included for these analyses (damage types 27 and 28, representing "hardwood" and "softwood"). Tree damage points were rasterized by maximum damage category and maximum 3-s gust to 1 km^2 pixel resolution. Maximum 3-s gust indicates the estimated strongest gust speed of the tornado associated with the damage point. These data yielded a total of 28,449 tree damage points related to tornados and 6,541 tree damage points related to thunderstorms, including 19,450 hardwood tree damage observations and 15,562 softwood (or thereafter, pine tree) damage observations.

Independent predictor variables fell into three main categories: terrain, soil, and climate (S1). 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, convergence index, diurnal anisotropic heating, LS factor (slope and length steepness factor), slope, slope position, terrain ruggedness index, topographic wetness index, total catchment area, valley depth, and wind exposition index. In addition, distance from coast was calculated for each 1 km^2 pixel. Soil data were collected from the USDA State Soil Geographic Database (STATSGO) including available water storage capacity in the top 250 cm of soil, a surface soil erodibility factor, depth of bedrock, pH of soil top layer, permeability and bulk density, and rasterized to 1 km^2 resolution. Historic climate data values averaged for the period between 1970 and 2000 were obtained from Worldclim.org, and included mean, minimum and maximum annual temperatures, average diurnal range (mean of monthly max temp − min temp), Isothermality [(Diurnal Range/Annual Range) * 100], temperature seasonality (standard deviation × 100), as well as mean temperatures of the wettest, driest, warmest, and coldest quarters each year. Precipitation variables included annual precipitation, seasonal precipitation (coefficient of variation), as well as precipitation of the wettest and driest month, and precipitation of the wettest, driest, warmest, and coldest quarters each year.

Tree damage is categorized by NOAA based on a score of 1–5, with score of 1 representing small limbs broken (up to 2.5 cm diameter), 2 indicating large branches broken (2.5–7.5 cm diameter), 3 representing trees uprooted, 4 indicating trunk breakage and 5 indicating trees debarked with only stubs of largest branches remaining (McDonald and Mehta 2004). For the purposes of our analysis, we merged these five categories into three categories as follows: (1) branch damage—NOAA category 1 and 2 together; (2) uprooting—NOAA category 3 alone; and (3) trunk breakage—NOAA categories 4 and 5 together. It is notable that category 5 is an extremely rare event, and only eight data points in the data set of 28,449 represented this damage.

Statistical analyses

The analyses were conducted in two steps as follows: (1) we first selected the most important predictors that could discriminate between consecutive damage classes; and (2) once predictors were found, we fitted a multinomial model that separated all classes as a function of the predictors found in the first step. To select the variables associated with damage categories, we utilized a Generalized Additive Model (GAM), to avoid making parametric assumptions about the form of the response. The GAM framework, as implemented in the 'gamsel' package in R (Chouldechova et al. 2018), sequentially penalizes a likelihood function to automatically select the most important linear and non-linear predictors. This framework allows each variable to be estimated as null, linear, or low-complexity curve in a non-parametric manner as given by the data. The GAM framework was chosen as we expected that some terrain, climate and soil variables would display non-linear relationships with damage class. A generalized additive model is an extension of the linear model which allows the effects of the predictor variables to be captured through smooth functions. This allows detection of linear or non-linear patterns in the data. GAMSEL utilizes a LASSO (Least Absolute Shrinkage and Selection Operator) type of regularization method that penalizes regression coefficients with poor predictive powers, shrinking them towards zero while finding the strength of the regularization term sequentially using tenfold cross validation against a training set of 80% of the data to select the optimal model. This process reduces overfitting and removes extraneous and highly correlated variables. The response variable was assumed to be binomially distributed for each damage level, beginning with branch damage set to zero and both uprooting and trunk breakage levels set to one, followed by the branch and uprooting damage categories set to zero and the trunk breakage category set to one. The GAMSEL process was applied to in this manner to determine which variables were separating the lower vs. higher levels of damage. A tuning parameter (gamma) was set to 0.5 to penalize linear and non-linear components equally, and each variable was allowed 10 basis functions and a maximum of seven degrees of freedom to allow some flexibility while limiting overfitting of non-linear forms. Variables selected via this process were then utilized in a second step using a multinomial Generalized Additive Model (GAM) as implemented in the "mgcv" package in R (Wood 2017). Smoothing splines were applied to estimate the non-parametric functions for all selected variables except for windspeed, for which a tensor product smooth was applied. For a multinomial GAM, categories must be coded as 0 to K, so that there are K + 1 categories and K linear predictors. In our model, branch damage was coded 0, uprooting damage was coded 1, and trunk breakage was coded 2, thus K = 2 with three categories and two linear predictors. Each predictor depends on smooth functions of predictor variables, in this case the variables selected via the GAMSEL as separating low damage category from the higher damage categories (uprooting or trunk breakage), and the variables separating the uprooting category from the trunk breakage category. Predictions were then generated across the region using the selected predictor variables for terrain, soil, and climate, and using average windspeeds from historical NOAA tornado path data. Errors were calculated from the logit values, and predictions on the response scale (probability) were generated. Response scale predictions were then multiplied by event probability to give an overall probability of damage at each level (low, uprooting, or trunk breakage). For example, if the risk of uprooting during an event is 0.7 and the risk of a tornado or severe thunderstorm event given the historical records is 0.01, then the total immediate risk of experiencing an uprooting event is $(0.7 \times 0.01) = 0.007$, or 0.7%. Finally, to capture the increasing probability damage at each level across 10, 20, and 30 year intervals, the conditional probability of damage at each level (A), given no damage event occurred in the prior interval (B), was calculated by multiplying the probabilities as follows:

$$P(A|B) = \left\{1 - \left[(1-p)^t\right]\right\} * 100$$

where p = the immediate event probability and t = the amount of time in years. This process was applied for pine and hardwood tree damage separately (Fig. 1). The interval length was chosen based on typical rotation time of managed forests in the southeastern U.S. is 20–30 years. Thus, in our previous example, the immediate probability of 0.7% would be 20% conditional probability in 30 years given no event has occurred during that 30 year period. The 1 km^2 resolution was used for all analyses. For visualization purposes, maps for tree damage probability were interpolated using bilinear interpolation, and then aggregated and smoothed with a focal operation with a factor of 10.

Results

Landscape-scale patterns of wind event probability

The probability of tornadic events based on the 70-year history of data revealed hotspots of tornadic activity in the southeastern U.S. Parts of Oklahoma and Arkansas, along with the mid-south from southern Mississippi through northern Alabama showed a higher probability of tornadoes (Fig. 2a). When examining the spatial pattern of tornado magnitude (Fig. 2b), the mid-south was prominent again as an

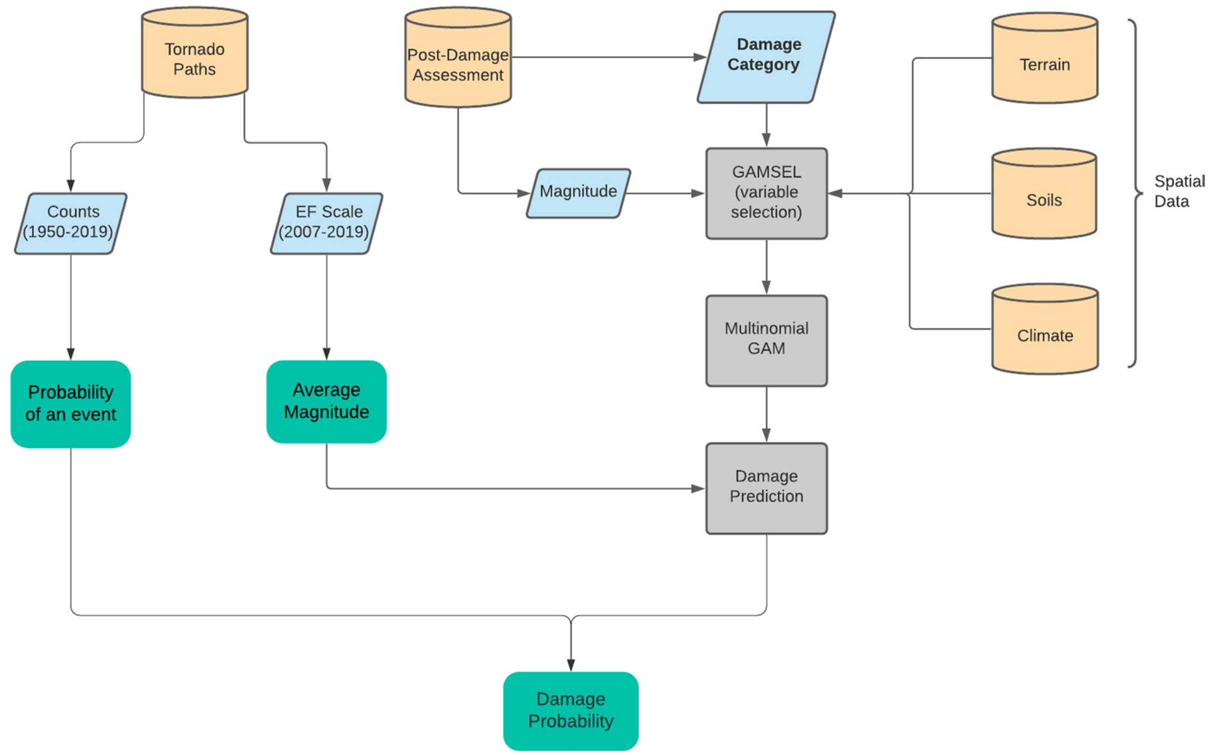

Fig. 1 Model process workflow for our study on assessing wind risks in the southeastern U.S. forests. *GAMSEL* generalized additive model selection, *GAM* generalized additive model, *EF* measure of tornado magnitude

area of not only high probability, but also higher magnitude tornadoes, particularly in Alabama. Areas closer to the coast, even those which experience frequent tornados such as parts of Florida and coastal Texas, had on average much lower magnitudes than inland areas.

Variables discriminating between damage classes

For pine trees, seven variables were identified as predictors of damage beyond broken branches (including uprooting or trunk breakage). Those variables included windspeed, slope, valley depth, bedrock depth, average temperature of the warmest quarter, precipitation in the coldest quarter, and longitude. Variables which separated trunk breakage from uprooting included windspeed and soil erodibility factors. All variables included in the final model were significant predictors of damage level (Table 1). The model explained 53% of the deviance. Not surprisingly, the likelihood of pines experiencing uprooting and/or trunk breakage damage categories increased with increasing windspeed, but also increased with higher temperatures in the warmest quarter and precipitation in the coldest quarter. Damage category increased slightly on slopes between 10° and 30°, and decreasing slightly on steeper slopes. An intermediate bedrock depth between 102 and 127 cm (40 to 50 inches) was related to higher damage category. Damage category tended to decrease with increasing valley depth (Fig. 3). Windspeed was the primary variable separating trunk breakage and uprooting as higher windspeeds increased the chance of trunk breakage, while a high soil erodibility factor decreased the chance of trunk breakage, making uprooting a more likely scenario in highly eroded soils (Fig. 4).

For hardwood trees, seven variables were identified as predictors of damage beyond broken branches (including uprooting or trunk breakage). Those variables included windspeed, valley depth, soil pH, isothermality, average temperature of the driest quarter, precipitation in the coldest quarter, and longitude. The variables which separated trunk breakage from uprooting included windspeed, distance

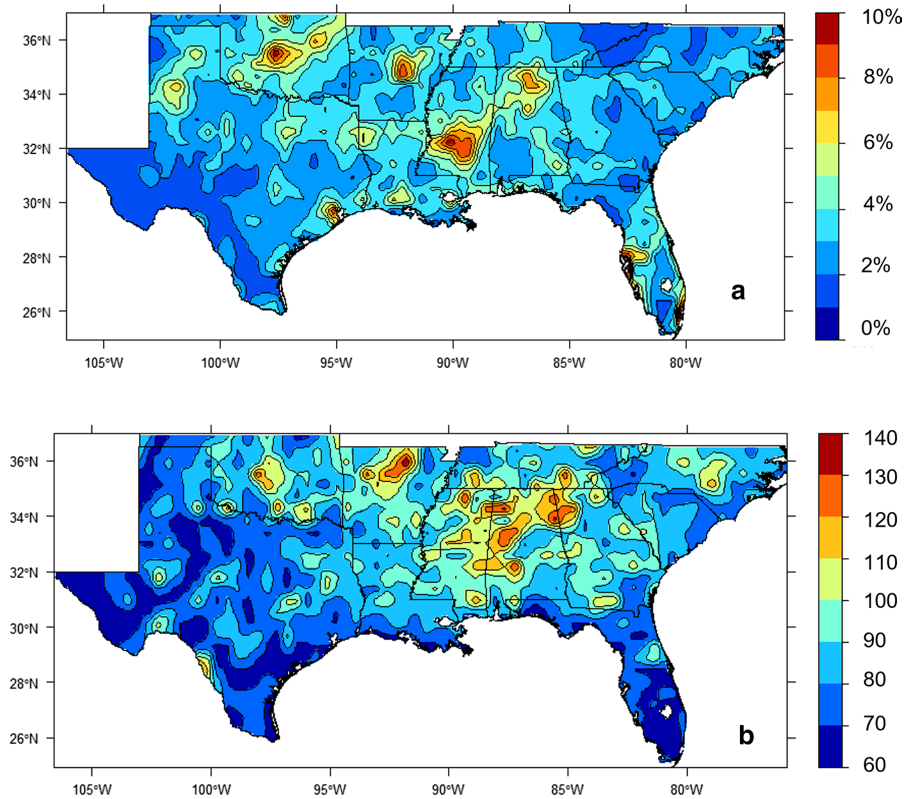

Fig. 2 **a** Probability of tornadic events based on 70 year history in the southeastern U.S. Scale represents total probability, expressed in percent. **b** Average magnitude of tornado based on EF scale for all tornadoes for years 2007–2019 in the southeastern U.S. Scale represents the average 3-s gust of tornado events in miles per hour

from the coast, soil erodibility factor, and longitude. Precipitation in the coldest quarter and isothermality were not significant predictors of damage level in the final model (Table 1), all other variables were significant predictors. The model explained 60.9% of the deviance. The likelihood of hardwoods experiencing damage categories of uprooting and/or trunk breakage increased with increasing windspeed, and also when average temperatures in the driest quarter were > 10 °C. Damage category tended to decrease with increasing valley depth, and decreased when soil pH was > 6.5 (Fig. 5). Windspeed was the primary variable separating trunk breakage and uprooting, with higher windspeeds increasing the chance of trunk breakage, while soil erodibility was not significant in separating trunk breakage and uprooting for hardwoods as it was for pine trees (Fig. 6).

Predictive models of wind damage in forests

Predictions of different levels of damage showed broad spatial patterns, with very similar patterns for both pine and hardwood trees (Figs. 7, S2, S3). Branch damage was more common in northwest Texas and in areas closer to the coast, where tornadoes tend to be lower in magnitude. Uprooting damage showed hotspots in southern Mississippi and mid Arkansas, with scattered patches of higher probability through much of the mid-south and Oklahoma. The areas with highest probabilities of trunk breakage aligned with the areas of areas associated with highest event probabilities and highest magnitude tornadic activity, primarily the mid-south through Mississippi and Alabama, and parts of Arkansas and Oklahoma. When projected forward to 10, 20, and 30-year probabilities, parts of the mid-south, mid-Arkansas and Oklahoma exceeded a 60% probability of either uprooting or trunk breakage for pine trees in within 30 years (Fig. 8). For hardwood trees, a portion of southern Mississippi shows > 50% probability of uprooting within 30 years, along with scattered patches in Alabama, Arkansas, and Mississippi, while hardwood trunk breakage shows > 50% probability of within 30 years concentrated in a portion of northern Alabama and north-central Arkansas, areas where tornadoes have also been historically higher in

Table 1 Generalized Additive Model (GAM) results for tree damage

Smooth (variable)	Tree type	edf	Ref.df	Chi.sq	p value
te (Windspeed)	Pine	3.444	3.522	714.83	< 0.001
s (Slope)	Pine	2.326	2.943	10.13	0.016
s (Valley depth)	Pine	5.651	6.884	58.69	< 0.001
s (Bedrock depth)	Pine	3.709	4.47	38.03	< 0.001
s (Mean temp. warm Q.)	Pine	1.001	1.001	13.75	< 0.001
s (Precip. cold Q.)	Pine	4.709	5.815	34.71	< 0.001
s (Long.x)	Pine	1.001	1.002	25.49	< 0.001
te.1 (Windspeed)	Pine	3.371	3.45	675.58	< .0001
s.1 (Soil erodibility index)	Pine	6.608	7.401	126.69	< 0.001
te (Windspeed)	Hardwood	1.732	2.07	629.419	< 0.001
s (Valley depth)	Hardwood	6.325	7.556	59.594	< 0.001
s (pH)	Hardwood	3.392	4.176	15.832	0.004
s (Isothermality)	Hardwood	2.774	3.58	10.38	0.027
s (Mean temp dry Q.)	Hardwood	5.328	6.484	27.45	< 0.001
s (Precip. cold Q.)	Hardwood	4.647	5.819	9.303	0.15
s (Longitude)	Hardwood	7.115	8.016	54.53	< 0.001
te.1 (Windspeed)	Hardwood	3.921	3.951	780.726	< 0.001
s.1 (Distance from coast)	Hardwood	1.001	1.003	11.645	< 0.001
s.1 (Soil erodibility index)	Hardwood	1.005	1.01	0.126	0.73
s.1 (Longitude)	Hardwood	7.163	8.116	141.796	< 0.001

Non-parametric smooth terms include tensor (te) or smoothing spline (s), *edf* effective degrees of freedom, *Ref.df* reference degrees of freedom (used in computing test statistic and the p values). The variables indicated by te(variable) or s(variable) explain damage beyond broken branches (uprooting or trunk breakage), the variables indicated by te.1(variable) or s.1(variable) are those which separate uprooting from trunk breakage. *Mean temp. warm Q.* the average temperature of the warmest quarter of the year; *Mean temp. dry Q.* the average temperature of the driest quarter of the year; *Precip. cold Q.* precipitation in the coldest quarter of the year

magnitude (Fig. 9). As a general trend, trunk breakage appears more likely for pine trees and uprooting more likely for hardwoods, but this general trend depended on location and storm intensity.

Discussion

Our study provides the first regional assessment of tree damage risk in the southeastern U.S. based on tornadic history of the region, damage assessments, and landscape attributes. We found that terrain characteristics of slope and valley depth can contribute to damage severity, along with soil characteristics such as erodibility factors, soil pH, and bedrock depth. In addition, climatic variables including average wind gust speed, average temperatures, and precipitation can also influence tree damage levels. We found that areas in the mid-south through Mississippi and Alabama, and portions of central Arkansas and Oklahoma had increased probabilities of more severe levels of tree damage (uprooting and trunk breakage) which has implications for forest restoration and resilience activities in these states.

Climatic, landscape, and stand level predictor variables were variously important and different for pine and hardwood trees. Precipitation, in particular in the coldest quarter, was a selected predictor for both pine and hardwood tree damage, but interestingly showed opposite patterns for tree-types with increased risk for pine and decreased risk (though non-significant) for hardwood trees. This is consistent with observations that soil characteristics can interact with tree species vulnerability. Some hardwood species such as mesic and xeric oaks are often more vulnerable to wind damage in drier soils, while certain pine species, such as slash pine and loblolly pine, are more vulnerable to wind damage in wetter soils (Rutledge et al. 2021). In the current study higher temperatures during the dry quarter were associated with increased

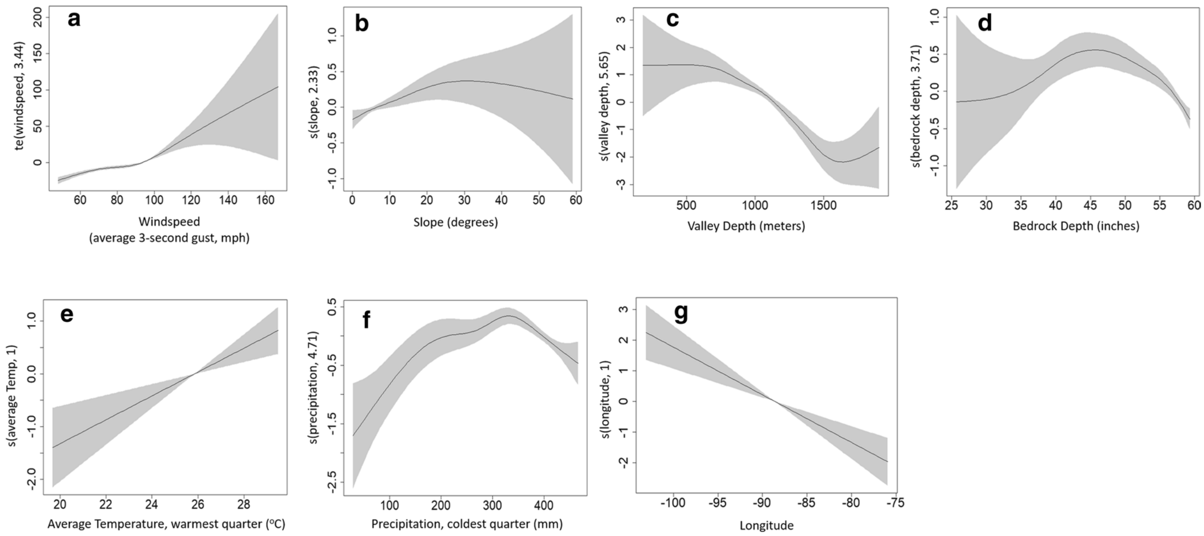

Fig. 3 Variables separating branch damage from higher damage categories (uprooting or trunk breakage) for pine trees in the southeastern U.S., including the average 3-s gust windspeed associated with tornado or severe thunderstorm (**a**), slope (**b**), valley depth (**c**), bedrock depth (**d**), average temperatures in the warmest quarter of the year (**e**), precipitation in the coldest quarter of the year (**f**), and longitude indicating the partial effects of along the longitudinal axis (**g**). Grey area represents standard errors. Y axis indicates the partial effect of the predictor variable on damage level. Y axis label indicates: smoothing function (predictor variable, effective degrees of freedom). Effective degrees of freedom = 1 indicates a linear relationship, higher effective degrees of freedom represent a non-linear relationship

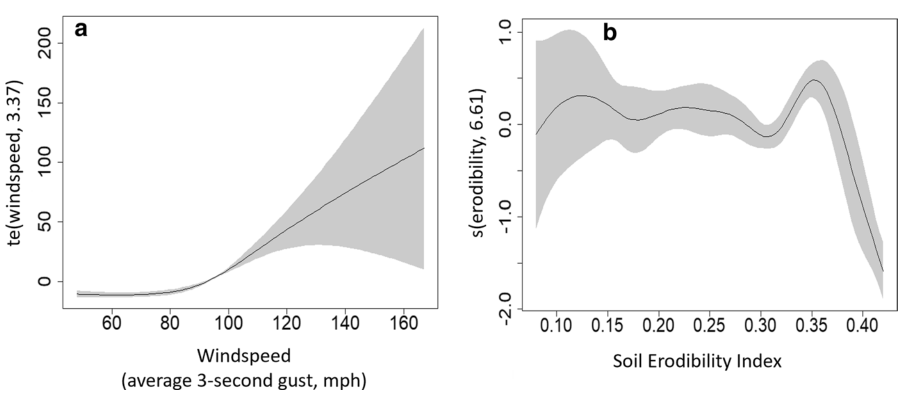

Fig. 4 Variables separating uprooting and trunk breakage for pine trees in the southeastern U.S., including the average 3-s gust windspeed associated with tornado or severe thunderstorm (**a**), and soil erodibility index (**b**). Grey area represents standard errors. Y axis indicates the partial effect of the predictor variable on damage level. Y axis label indicates smoothing function (predictor variable, effective degrees of freedom). Effective degrees of freedom = 1 indicates a linear relationship, higher effective degrees of freedom represent a non-linear relationship

damage severity for hardwood trees, suggesting a general that dry soils increased damage risk for hardwoods, but this would not necessarily hold true for all of them. Given that we do not have more detailed species data beyond 'hardwood' vs. 'pine', it is difficult to draw conclusions from these results beyond a general understanding that tree species may interact with the degree of soil wetness. Soil pH was related to higher probabilities of uprooting for hardwoods in soils with higher acidity (or lower pH). Similarly, studies in Europe have found soil pH to be a significant factor related to damage after storm events,

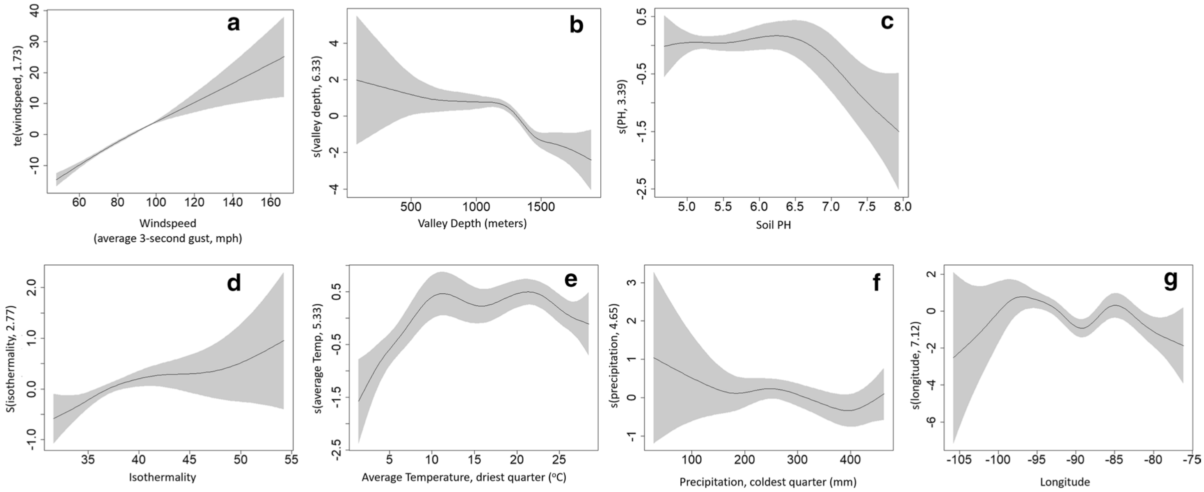

Fig. 5 Variables separating branch damage from higher damage categories (uprooting or trunk breakage) for hardwood trees in the southeastern U.S., including the average 3-s gust windspeed associated with tornado or severe thunderstorm (**a**), valley depth (**b**), soil pH (**c**), isothermality (**d**), average temperatures in the driest quarter of the year (**e**), precipitation in the coldest quarter of the year (**f**), and longitude, indicating the partial effects along the longitudinal axis (**g**). Grey area represents standard errors. Y axis indicates the partial effect of the predictor variable on damage level. Y axis label indicates smoothing function (predictor variable, effective degrees of freedom). Effective degrees of freedom = 1 indicates a linear relationship, higher effective degrees of freedom represent a non-linear relationship

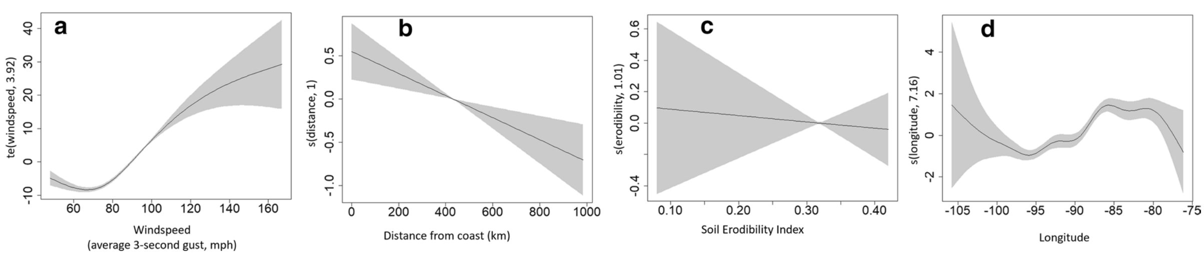

Fig. 6 Variables separating uprooting and trunk breakage for hardwood trees in the southeastern U.S, including the average 3-s gust windspeed associated with tornado or severe thunderstorm (**a**), distance from the coast (**b**), soil erodibility index (**c**), and longitude, indicating the partial effects along the longitudinal axis (**d**). Grey area represents standard errors. Y axis indicates the partial effect of the predictor variable on damage level. Y axis label indicates smoothing function (predictor variable, effective degrees of freedom). Effective degrees of freedom = 1 indicates a linear relationship, higher effective degrees of freedom represent a non-linear relationship

with greater damage in areas of higher soil acidity, although the reason for this relationship is poorly understood (Mayer et al. 2005). Bedrock has also been noted as a factor in tree damage, as shallower bedrock often facilitates stability for trees which are able to penetrate the bedrock, reducing uprooting potential, though sometimes increasing trunk breakage potential (Foster and Boose 1992; Loope et al. 1994). In another instance, 93% of uprooted trees (mostly pines) after a tornado in Arkansas were found to have penetrated the bedrock (Phillips et al. 2008). Hence, this effect can be variable based on tree species and the type of bedrock, and the capacity for very deep rooting in deep soils can have the same effects (Peterson 2000a). In our study, deeper bedrock increased damage risk for pine and not for hardwood trees, and it could be due to different rooting strategies for these tree-types. While there is significant variability in rooting depth among species, a general trend is that hardwood species have the capacity for deeper rooting compared to pine species, although this can also vary based on soil moisture and depths

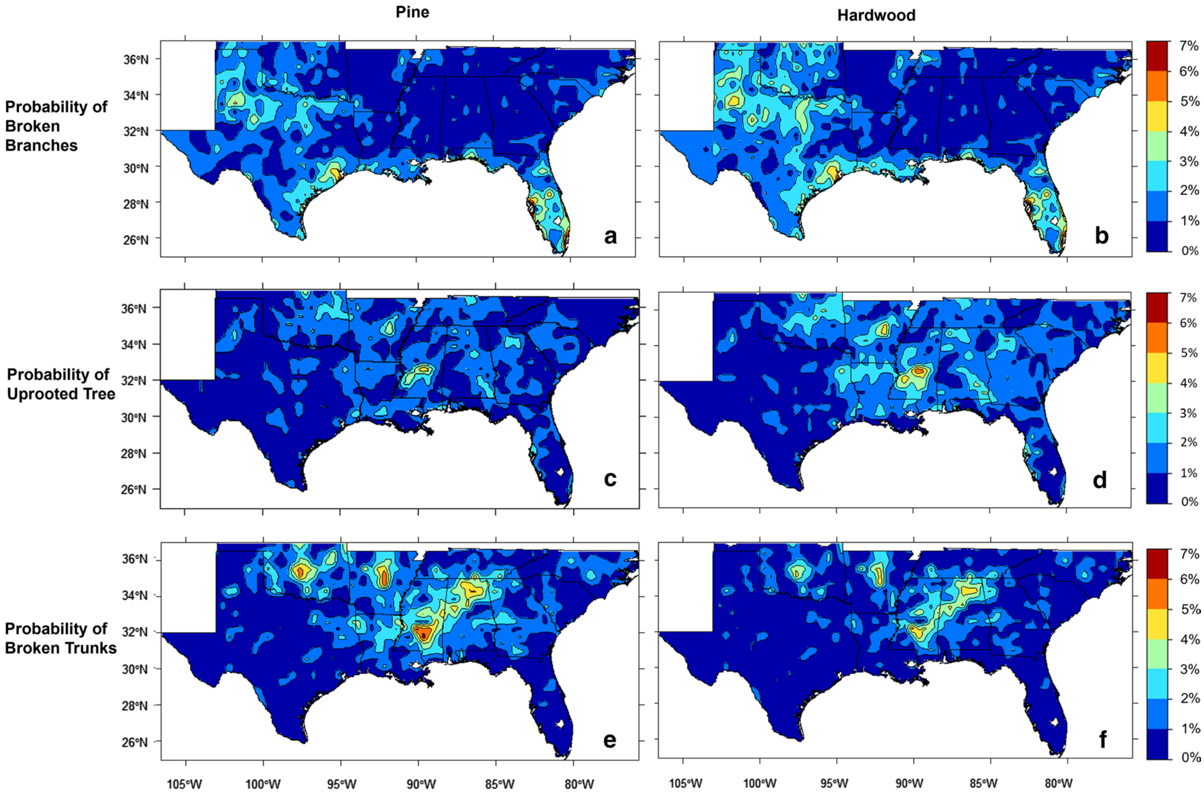

Fig. 7 Predicted probabilities of broken branches (top row: **a**, **b**), uprooting (middle row: **c**, **d**), and trunk breakage (bottom row: **e**, **f**) for pine trees (left column: **a**, **c**, **e**) and hardwood (right column: **b**, **d**, **f**). Interpolated predictions were created through a multinomial generalized additive model. Scale represents total probability and are expressed in percentages

of the water table (Fan et al. 2017). While generalizations are difficult without tree species identifications in the data set, it is possible that bedrock depth is not a significant factor for hardwoods due to their capacity to reach deeper bedrock, while pines are more sensitive to bedrock depth due to shallower rooting.

Slope had a very moderate influence on the damage category and for pine trees only, there was increased damage on moderate slopes of 10° to 30°. Previous research has indicated that greater damage occurred as tornadoes descended slopes and less damage as they ascended slopes (Cannon et al. 2016). This could be part of the reason slope does not stand out in this analysis, as the damage level would depend on the slope's relation to the path of the tornado. While most tornados in this region have a general southwest to northeast direction (Thom 1963), aspect was also not an important factor in predicting tree damage. Other studies have noted variability between these factors and storm intensity based on location and storm characteristics (Frazier et al. 2019; Houser et al. 2020). It is possible that the slope/aspect relationship deserves more focused attention in localized risk assessments, and a broad regional approach such as our study may be insufficient for elucidating a clear relationship between those variables and damage risk.

Our models explained 53% and 61% of the deviance for pine and hardwood trees, respectively. This indicates a moderate fit for the models, with terrain, climate, and soil variables explaining over half of the variability in damage levels. The remaining variability is likely based on local variables such as tree height, diameter, crown shape, etc., and thus landscape level variables will generally be limited in their ability to account for substantial deviance. Nonetheless, we observed some broader spatial patterns which can be useful to land managers, and they can be integrated into their local risk analysis considering tree and stand structure characteristics.

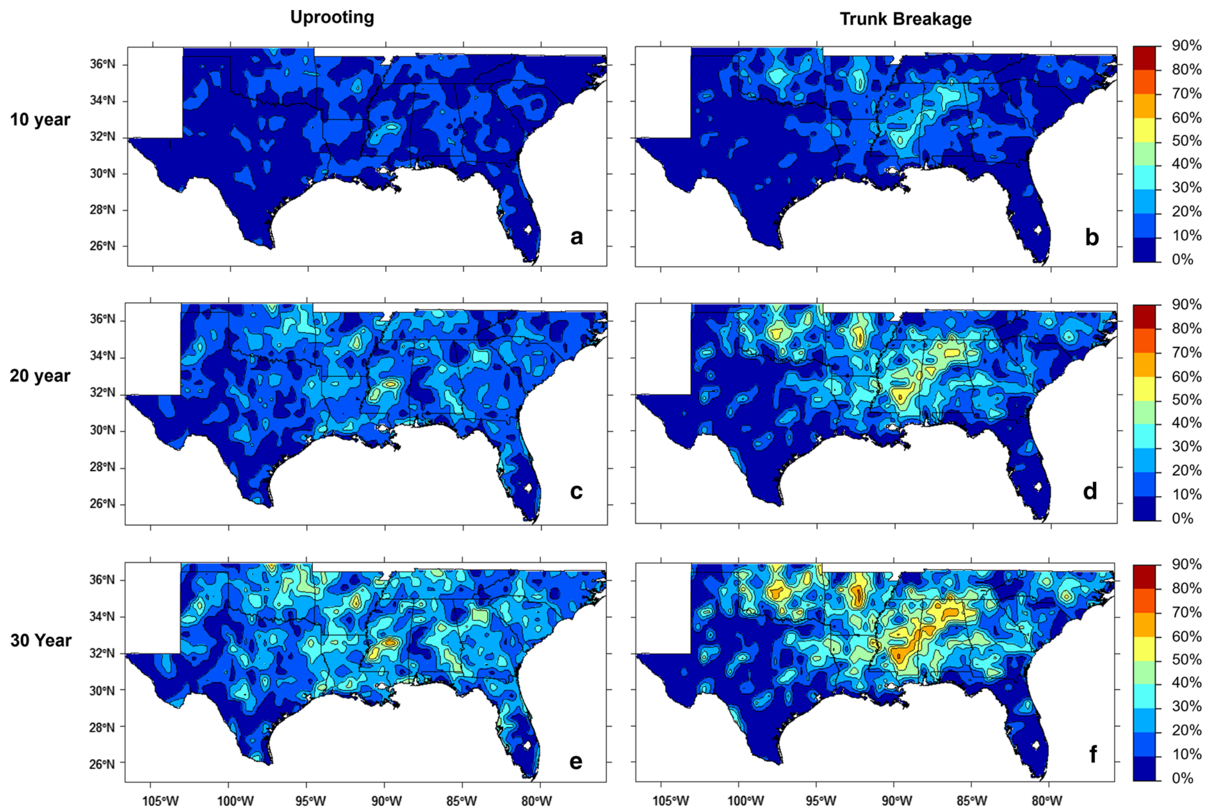

Fig. 8 Projected damage probabilities for pine trees: probability of uprooting (left column: **a**, **c**, **e**) and trunk breakage (right column: **b**, **d**, **f**), at 10 years (first row: **a**, **b**), 20 years (second row: **c**, **d**), and 30 years (third row: **e**, **f**). Projections based on response-scale predicted probabilities of each damage level generated by a multinomial generalized additive model, and projected based on $\left\{1-\left[(1-p)^t\right]\right\} * 100$, where p = the total event probability and t = the amount of time in years

The frequency and strength of tornadoes through the mid-south area from Mississippi through Alabama has been noted in meteorological literature, and the area has been dubbed "Dixie Alley" (Dixon et al. 2011; Ashley and Strader 2016; Frazier et al. 2019). This area of the mid-south and has been noted as an area of high risk for tornadoes, potentially even higher than the great plains (Coleman and Dixon 2014) Given the Southeast also contains about a third of total U.S forest area (Oswalt and Smith 2014), it stands to reason that this mid-south region would experience higher risks of tree damage given both higher frequency and magnitude of tornadic events along with significant area of forest land. There were only minor differences between the spatial patterns of predicted damage to pines vs. hardwoods, but the differences between spatial patterns of the type of damage were striking. Higher damage categories for both hardwood and pine trees were observed through the mid-south, with uprooting hotspots appearing in southern Mississippi and central Arkansas, and trunk breakage hotspots extending into northern Alabama and central Oklahoma. Hence, differential management of stands under wind disturbances as based on location may be a future consideration.

For the most part, the immediate damage probability did not exceed 5% with the exception of uprooting probability for hardwood trees (highest overall probability 6%), and broken trunks for pine trees (highest overall probability 7%). However, a typical stand rotation of 25–30 years would experience successively increasing risk over time, and the longer a stand has gone without a disturbance event, the more likely a disturbance event will occur. It is hence, useful for land managers to know their relative risk with time, which will not be equal in all locations. Areas which show a high relative risk within a 30 year time frame may consider damage mitigation within their

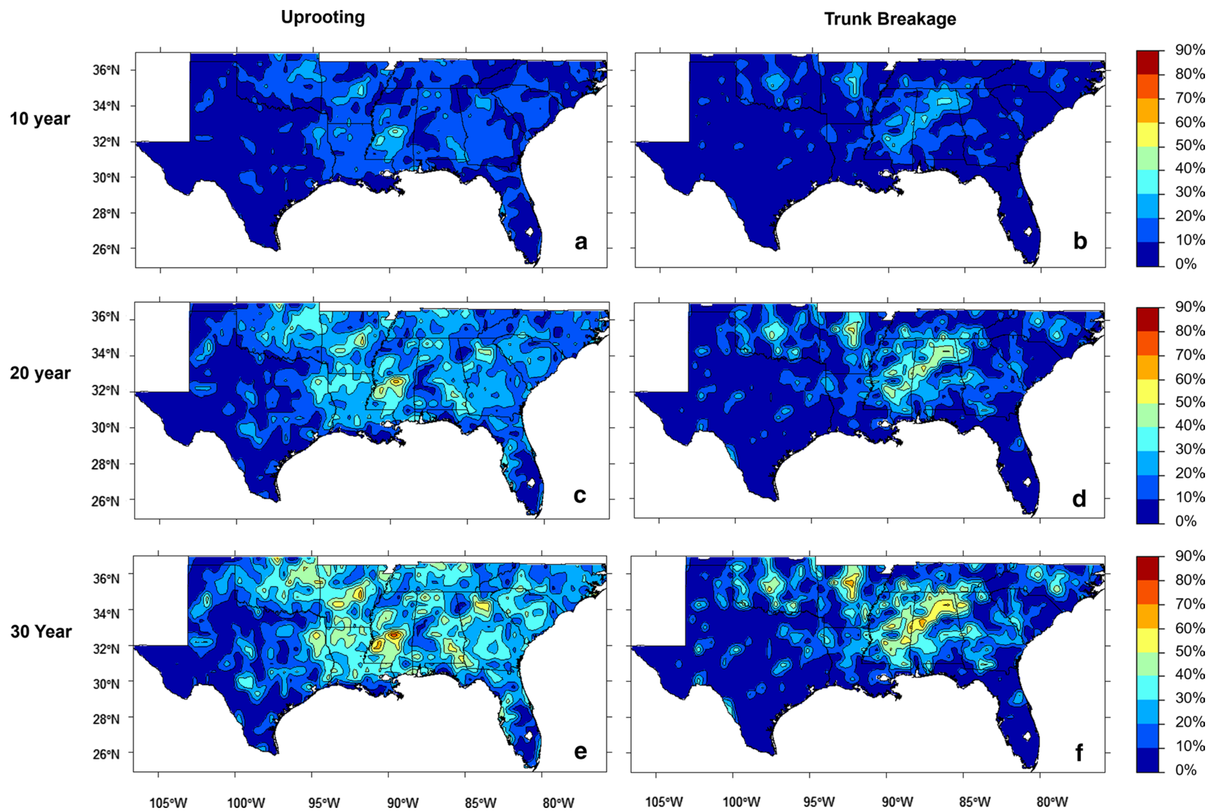

Fig. 9 Projected damage probabilities for hardwood trees: probability of uprooting (left column: **a**, **c**, **e**) and trunk breakage (right column: **b**, **d**, **f**), at 10 years (first row: **a**, **b**), 20 years (second row: **c**, **d**), and 30 years (third row: **e**, **f**). Projections based on response-scale predicted probabilities of each damage level generated by a multinomial generalized additive model, and projected based on $\left\{1-\left[(1-p)^t\right]\right\}*100$, where p = the total event probability and t = the amount of time in years

risk management plan for each rotation. Understanding the likely types of damage can also be helpful for risk mitigation, as salvage operations for uprooted trees vs. broken trunks may have differential costs associated with them.

Our study's projections are only relative to tornado or severe thunderstorm damage, and do not include hurricanes and tropical storms. Areas like south Florida, costal Texas, and coastal Louisiana may be at low risk for tornado damage, however these areas are likely to have higher risk from hurricane and tropical storm damage. Future risk assessments will incorporate hurricane damage risk for a more complete overview of windthrow tree damage throughout the southeastern U.S. We chose to focus first on tornados whose patterns are less predictable, and tend to do more damage to inland forests. In addition, it is important to note that these damage probabilities indicate the likely level of damage (broken branches, uprooting, or trunk breakage) but do not predict the percent of treefall within a stand. This is because the current EF scale post-damage assessments do not account for percent of treefall in an area, only the type of damage. Satellite and remote sensing methods are now making it possible for more precise assessments of treefall damage for EF scale estimates, even in remote areas, rather than on the ground observations (Godfrey and Peterson 2017). As this more precise and inclusive data are being gathered over time, future models will increase the precision of the current estimates.

A limitation of the current study is the lack of detail relating to tree characteristics associated with the NOAA damage data set beyond "hardwood" or "pine" trees. A more precise model would include tree attributes such as age class, height, diameter, and species. Future work may refine these models and improve the deviance explained by incorporating these variables if sufficient data are collected or becomes available. The variable selection process for determining predictors of damage utilized in these analyses can also be applied to other types of damaging events when post-storm damage data are available for such predictive purposes. The purpose of these analyses was not to make precise predictions of tornado events, but to provide landowners and managers with some insight as to the relative risk of tree damage given their location, recognizing that local factors and stand characteristics will also influence their risk profile. While this current risk estimation is incomplete, owing to the lack of tree-specific data, it provides an important piece of the risk puzzle, which is landscape-level patterns of tree damage and risk, and an understanding of terrain, climate, and soil conditions which can interact with damage level. Forestry systems require long term, often multi-generational planning, and an understanding risk relative to the frequency and type of tree damage in one's area can facilitate long-term planning and risk abatement. Tornadoes are difficult events to predict with any precision, and the occurrence of a tornado or severe thunderstorm event does not inherently mean damage will be severe. Yet, we noted some general spatial patterns in the type and severity of damage that are non-random and give some insight into relative risk associated with these catastrophic events in southeastern U.S. forests.

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Author contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by CCF and CRM. The first draft of the manuscript was written by CCF and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data availability The datasets compiled and analyzed during the current study are available from sources indicated within the manuscript or from the corresponding author on reasonable request.

Declarations

Competing interest The authors declare that they have no competing financial interests that could have appeared to influence the work reported in this paper.

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