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Understanding hurricane effects on forestlands: Land cover changes and salvage logging

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ABSTRACT

Hurricanes can cause catastrophic damage to forestlands, prompting forest owners to engage in salvage logging to mitigate losses and resulting in a sudden and pronounced impact on the timber supply. At the same time, salvaging efforts have profound ecological repercussions, reshaping forest dynamics and affecting vital ecosystem processes. Given the relevant impact of salvage logging to the timber market and its potential ecological effects, evaluating the main factors motivating or limiting its occurrence and the common spatial patterns of salvage sites could offer valuable support for post-storm management efforts following future hurricane events.This study evaluates the land cover change (LCC) of forested areas following hurricanes, recognizing that the change to land cover classification could be derived from storm damage or additional modifications, such as salvage logging activities. We used a set of predictive machine learning models to investigate the primary factors influencing these modifications and determining a possible connection to salvage operations. To serve this purpose, we selected variables that relate to both forest's vulnerability to hurricane disturbance and salvage site selection criteria. This research was centered primarily on the category-five Hurricane Michael, using three additional hurricanes of different intensities to compare results. Random Forest was the bestperforming model for predicting LCC in all cases, having wind speed and distance to nearest wood-consuming mills as the most important features when trained on Hurricane Michael data, emphasizing the relevance of market- and operation-related variables alongside weather disturbance aspects. The findings of our study lead us to infer that the observed modifications in land cover following hurricanes likely represent an additional transformation induced by the removal of damaged timber material, potentially serving as a proxy for salvage logging activities.

1. Introduction

The forest products sector is among the major contributors to the economy of the southern United States (Brandeis and Hodges, 2015). With more than 40 % of the land covered by forests, encompassing over 90 million hectares (Dewitz and U.S. Geological Survey, 2021; U.S. Census Bureau. 2021), the region produces more than 50 % of the annual timber volume harvested in the U.S. (Brandeis et al., 2012). While having a crucial role not only on the forest products sector, but also in providing ecosystem services, forested landscapes in the southern United States face several challenges in the form of biotic and abiotic disturbance events, such as pest outbreaks, wildfires, and strong wind events (Costanza et al., 2023; Potter et al., 2019; Prestemon and Holmes, 2004). In particular, hurricanes can create considerable damage in forests due to their scale and severity (Rutledge et al., 2021; Stanturf et al., 2007). Hurricane Michael, for example, made landfall in Florida on October 10, 2018, and impacted 2.4 million hectares of forestland (Brandeis et al., 2022), causing over US$ 1 billion in timber losses in the

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state of Florida alone, with extensive destruction to forestland in Georgia and Alabama (Matteson, 2021).

Hurricanes effect on timber markets can be pronounced, with a price depression immediately after the storm, caused by the supply expansion during salvage operations, followed by a high-price period due to a shortage of timber inventory in the following years (Carter, 2017; Henderson et al., 2022; Kinnucan, 2016; Prestemon and Holmes, 2010; Sun, 2016, 2020). This fluctuation creates a temporary market disequilibrium, causing a redistribution of social welfare effect on forest stakeholders. At the same time, the severity and frequency of hurricanes can lead to long-term ecological changes. These changes range from modifying forest structure and species composition to influencing community dynamics and ecosystem processes, such as the forest's successional trajectory and its ability to sequester atmospheric carbon (Allen et al., 2012; Kenney et al., 2021; McNulty, 2002; Xi et al., 2008). Salvage operations have also been shown to affect subsequent stand structure and development, with impacts depending on specific circumstances, such as region, forest type, and disturbance severity (Fraver et al., 2017; Morimoto et al., 2019; Oldfield and Peterson, 2019; Royo et al., 2016). Given the relevant impact of salvage logging to the timber market and its potential ecological effects, evaluating the main factors motivating or limiting its occurrence and the common spatial patterns of salvage sites could offer valuable support for post-storm management efforts following future hurricane events.

Research on salvage logging has a strong focus on its consequences to ecological functions (e.g., Kleinman et al., 2019; Leverkus et al., 2018; Lindenmayer et al., 2008) and on its impact on forest resilience, such as affecting rates of recruitment and establishment of key species for forest's successional process (e.g., Emery et al., 2020; Leverkus et al., 2021; Royo et al., 2016; Taylor et al., 2017). Previous studies also assessed the economic effects of salvage harvesting and its decision-making process (Petucco et al., 2020; Prestemon andand Holmes, 2004, 2008; Stanturf et al., 2007). However, there is a gap in research aimed at spatially identifying these operations to refine the understanding of the economic and ecological ramifications of salvage logging.

Satellite-based remote sensing tools are commonly used to monitor timber harvesting and natural disturbances (Hird et al., 2021; Schroeder et al., 2011; Senf and Seidl, 2021; St. Peter et al., 2020; Wilson and Sader, 2002). However, identifying harvest sites in recently disturbed environments is a challenging task. Satellite imagery is often limited in terms of spatial and temporal resolution. Additionally, the contribution of harvested trees to canopy reflectance has already diminished prior to their removal, making it difficult to separate salvage cuts from the preceding changes caused by the disturbance (Healey et al., 2006; Sebald et al., 2021).

Monitoring land cover and its changes across space and time can be a useful approach to evaluate the effects of disturbance events (Dwomoh et al., 2021). Land cover change (LCC) patterns have been largely assessed for the conterminous United States (e.g., Homer et al., 2020) and for specific regions of interest (e.g., Pijanowski and Robinson, 2011; Zhai et al., 2020), as researchers try to understand the causes and effects of these changes. Usually associated with land use, meaning the human use of land, models for LCC are mostly focused on sustainable land-use planning (Mahiny and Clarke, 2012; Verburg et al., 2019) and have population and economic factors as the most cited drivers of change (Zhai et al., 2020). When assessing natural disturbances, studies on LCC are generally aimed at supporting the evaluation of ecological impacts on natural habitats or its consequences on regional climate (e.g., Grybas and Congalton, 2015; Hosannah et al., 2021).

In the period that follows a great natural disturbance like a hurricane, an intuitive interpretation for shifts in forest cover towards a non-forest classification is that they likely represent some type of damage at a stand level, such as defoliation and tree cover loss. Nevertheless, it is reasonable to consider an alternative explanation: these thematic changes might also reflect the subsequent removal of damaged timber from these areas, indicating the occurrence of salvage activities.

In this study, we used a set of predictive models to investigate the changes in land cover classification within forested regions following a hurricane, with the purpose of understanding the primary factors influencing these modifications and determining a possible connection to salvage logging activities. We propose the following hypothesis: if the shifts in land cover classification exclusively represent forest damage, then variables related to storm intensity and forest vulnerability are anticipated to emerge as the most important predictors of such changes, with proxies for economic or operational activity providing no additional significant predictive power. Alternatively, if there is a substantial amount of salvage being captured by land cover changes, we expect the significance of economic or operational variables to be highlighted when predicting these changes.

Our research not only advances our comprehension of post-disaster management dynamics but also carries broad implications. By potentially identifying salvage harvesting as a primary factor influencing changes in land cover classification, we provide pathways for developing predictive models based on historical LCC patterns resulting from past hurricanes. These predictive models could serve to anticipate the probable locations of salvage activities following future disturbance events, offering a foundation for effective management responses. Forest stakeholders can leverage this information to formulate optimized strategies aimed at improving salvage rates and subsequent economic returns for forest landowners, while also minimizing ecological impacts.

2. Methods

2.1. Study area

Our research is centered primarily on Hurricane Michael, a destructive category 5 hurricane that hit the Gulf Coast region in 2018, with a maximum sustained wind speed of 257 km h^{-1}. The study area spans the hurricane's path, from its landfall near Panama City on the northwestern coast of Florida on October 10, 2018, to where it weakened to a tropical storm in central Georgia. We limited the analysis to areas potentially affected by sustained hurricane-force winds (over 119 km h^{-1}), as defined by the National Hurricane Center (NOAA NHC, 2023), which totaled approximately 2350,000 ha in Florida, Georgia, and Alabama (Fig. 1). Forestlands covered approximately 60 % of this area, with a predominance of pine species (around 75 % of forested area) and complemented with hardwoods primarily confined to riparian zones. Much of the pine in the region consists of a cluster of commercially important species called southern yellow pine, mainly represented by slash pine (*Pinus elliottii*) and loblolly pine (*Pinus taeda*) (USFS FIA, 2023). Longleaf pine (*Pinus palustris*) is also among the dominant species (USFS FIA, 2023; Zampieri et al., 2020), being valued in restoration projects and commercially for pine straw production.

2.2. Land cover classification and land cover change (LCC)

We use the term land cover change (LCC) to denote changes in forest cover classification derived from satellite image interpretation. It is important to note that "land cover" refers specifically to the physical attributes of the land, while "land use" pertains to human activities on the land. Therefore, it is not the goal of this study to identify if the changes in land cover classification are persistent modifications in land use or just temporary changes related to hurricane disturbance or forest management practices. For instance, a forested area that experiences a reclassification of its land cover to barren land following a disturbance and salvage period may eventually regenerate into forest through natural processes or human activity. Nonetheless, for the purpose of this study, all forested areas exhibiting a change in thematic land cover classification were assessed and categorized as land cover change.

We determined the LCC using LCMAP (Land Change Monitoring, Assessment, and Projection) Collection 1.2 (USGS, 2021), a set of land cover mapping and change monitoring data products. LCMAP is

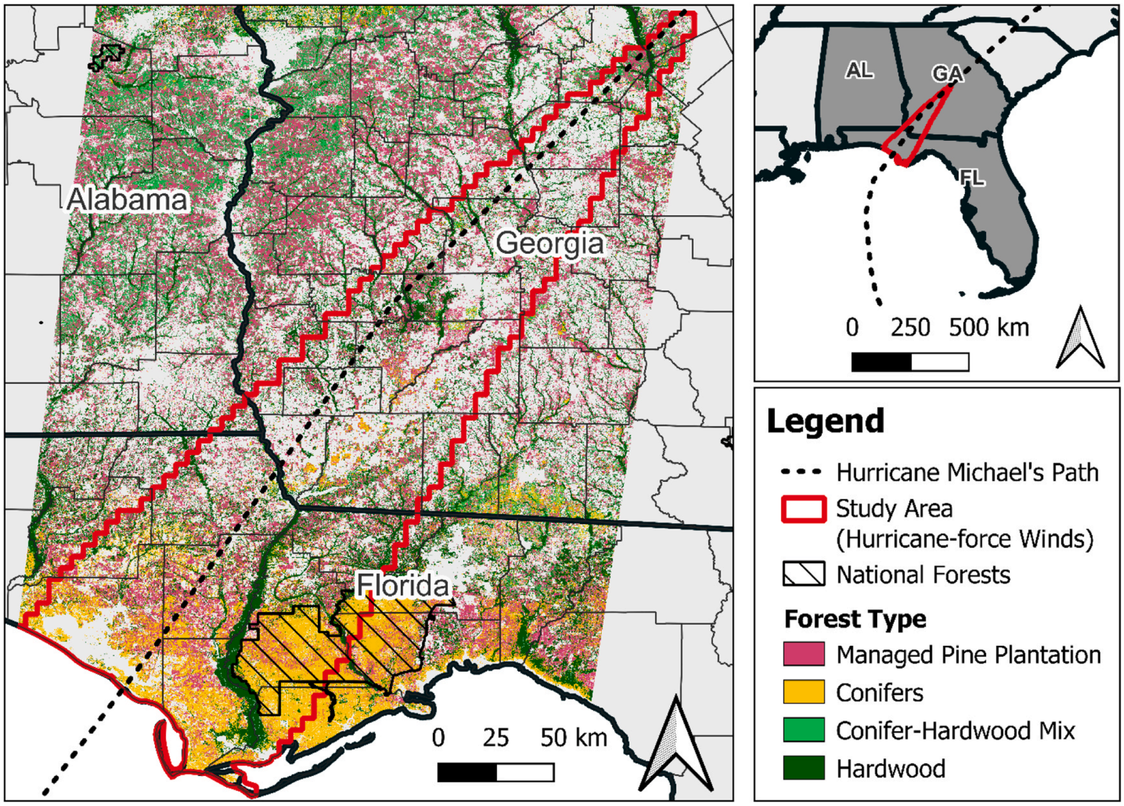

Fig. 1. Study area delimited by potential hurricane-force winds (NOAA NHC, 2023), with the forest type classification adapted from LANDFIRE (2020).

produced by the U.S. Geological Survey (USGS) based on Landsat imagery processed using the Continuous Change Detection and Classification (CCDC) algorithm (Xian et al., 2022; Zhu and Woodcock, 2014). LCMAP products have a spatial resolution of 30 m and are updated annually. The CCDC algorithm estimates a time series model for the spectral response of every pixel and detects “breaks” when multiple consecutive observations substantially differ from predictions (Zhu et al., 2020).

We compared the existing forests before and after Hurricane Michael’s occurrence and analyzed the areas that changed from the first condition in two ways: (1) subsequent land cover and (2) time of change. Forestlands were defined using LCMAP’s primary and secondary land cover maps (LCPRI and LCSEC), which are the first and second most likely land cover classes for the current product year, respectively. Since forested wetlands are sometimes classified as wetlands in LCPRI, but still as forests in LCSEC, we considered all “Tree Cover” classes in any of the two maps as forests, except in the case where any of the two maps indicate development, which indicates arborized urban areas. We used the LCPRI classification to determine the most likely subsequent land cover, and the spectral stability period (SCSTAB) map to evaluate the time of change.

The SCSTAB map indicates how long each pixel has the same land cover classification on LCMAP, with a reference date of July 1st of the map’s current year (USGS, 2021). Combining it with the successive land cover, we were able to visualize the land cover changes by date and type, and compare the rates of change during the year. Since classification changes to “Wetland” happened mostly in riparian zones, where precipitation has a significant effect on the water level, these changes were not considered in the analysis. As an attempt to capture only changes that were linked to the hurricane event, we limited the evaluation of forest cover change to the first quarter after its occurrence (90 days), which matches the period of higher salvage logging rates (Prestemon and Holmes, 2010; Sun, 2016).

We focused specifically on pine species due to higher salvage rates compared to hardwood stands (Brandeis et al., 2022). Using the 2016 Existing Vegetation Type (EVT) map from the Landscape Fire and Resource Management Planning Tools (LANDFIRE, 2020), we restricted our analyses to the forests classified as “Conifer” and “Managed Tree Plantation”. Given the predominance of pine species among other conifers in the region, particularly in commercially planted forests, we referred to these areas as managed pine plantations. The assessed forests were defined by overlaying the maps obtained from LANDFIRE and LCMAP. Data and processes used to calculate the land cover change of forest areas were summarized and illustrated in a flowchart (Figure A.1).

2.3. *Class imbalance*

The proposed methodology for LCC calculation resulted in a detected change in classification of 7.87 % (28,396 ha) of the forestlands inside our study area in the three months following Hurricane Michael. For binary classification models, which are used to label elements into two groups (e.g., changed or unchanged land cover), this proportion between classes constitutes a “class imbalance” problem, which might lead to poor performance of the models in predicting the low-represented (minority) class, often the one of most interest (Prati et al., 2009). We handled this issue by using the combination of two sampling methods: (1) SMOTENC (Synthetic Minority Over-sampling Technique for Nominal and Continuous) for oversampling the minority class (LCC=1) and (2) Tomek Links for under-sampling the majority class (LCC=0) (Chawla et al., 2002; Lemaitre et al., 2017). These techniques were applied only to the training subset, reaching a proportion close to 50 % of observations in each class, and leaving the test set unaltered.

2.4. *Explanatory Variables*

Based on previous studies (e.g., Bodaghi et al., 2018; Conrad, 2023; Feng et al., 2021; Fortuin et al., 2023; Gardiner, 2021; Hall et al., 2020; Kupfer et al., 2008; Rutledge et al., 2021; Wang and Xu, 2009) and on our understanding of storm-related biophysical processes, forestry operations and logistics, we tested nine variables (Table 1) that might influence the land cover change probability in forest areas, assuming this classification change might have occurred as a result of storm damage or salvage logging activities. These features cover the following main themes: hurricane characteristics, forest structure, market, and operational aspects. All variables were assessed at a 30 m spatial resolution to match LCMAP's products. Data with different resolution were resampled by averaging the values of nearest neighbors.

2.4.1. Hurricane characteristics

Wind is a significant cause of damage during hurricanes and its severity is dictated especially by its maximum sustained speed, which is also the measure used to classify hurricane categories (NOAA NHC, 2020). To account for the hurricane intensity at each point of the study area, we used the *hurrecon* package (Cannon, 2022) in R software to access the NOAA HURDAT2 database and employ the HURRECON model (Boose et al., 2001, 2004), generating a raster of maximum wind speed continuously along our study area. This model uses information on the track, size, and intensity of a hurricane, as well as the cover type (land or water) to estimate surface wind speed and direction.

A second feature related to hurricane's disturbance was the accumulated precipitation, calculated using daily data from the Global Precipitation Measurement (GPM) mission (NASA, 2019). Precipitation can exacerbate damage levels, with facilitated uprooting of trees in wet soils (Gardiner, 2021; Kamimura et al., 2012; Xi et al., 2008), and influence harvesting operations, making it less productive (Ezzati et al., 2021) and costlier in terrains with high moisture levels (Tavankar et al., 2021), thus less likely to happen. For this analysis, we considered the total hurricane-related rainfall and included a 15-days buffer prior to the date of landfall to account for possible oversaturation of soils in terms of moisture content, that could promote the uprooting of trees even with lighter winds.

2.4.2. Forest Structure

Forest structure can influence stand level damage severity due to strong wind events (Beach et al., 2010; Gardiner, 2021; Kupfer et al., 2008; Oswalt and Oswalt, 2008; Rutledge et al., 2021; Taylor et al., 2019). Forest stand attributes are also important elements in the selection of salvage areas, given that timber prices and forest value are largely dependent on the merchantability of timber. We selected basal area and stand age as explanatory variables capable of representing forest value and influencing forest susceptibility to damage. For instance, a mature low-density stand likely contains high-value trees, but their high canopy and elevated wind exposure may result in greater vulnerability to damage.

We used the *rFIA* package (Stanke et al., 2020) in R software to access and manipulate the Forest Inventory and Analysis data (USFS FIA, 2023), selecting plots located in a 15-km buffer around the study area and measured between 2017 and 2018. We calculated the basal area at the plot level for pine individuals with diameter at breast height over 5 in., and then performed an inverse distance weighted (IDW) interpolation to assign basal area values to all forested pixels. This process used 167 plots, of which 80 were inside the study area limits. The forest stand age was obtained directly from the CONUS Stocking-Age-Lorey's Height 2018 map (USFS FIA, 2022).

2.4.3. Market and operations

To evaluate the possible connection between salvage logging and the changes in forest cover classification, we included market and operational aspects that would potentially affect the site selection for salvage operations: (1) terrain's slope, (2) distance to the nearest road, (3) distance to the nearest mill with roundwood consumption, (4) local roundwood consumption, and (5) ownership type. The first three are associated with accessibility and operation and transportation costs, which can define the feasibility of salvaging specific areas. Terrain's slope was calculated in degrees using the SRTM (Shuttle Radar Topography Mission) Digital Elevation Data Version 4 (Jarvis et al., 2008). We used the 2021 RISI's Mill Asset Database (Fastmarkets, 2021) to set the location and annual consumption of mills, and the 2022 TIGER/Line Primary Roads National Shapefile (U.S. Census Bureau, 2022) to define the road network. To calculate the local roundwood consumption we first defined a procurement circle for each mill, proportional to their annual consumption (in tons year^{-1}). This proportionality was arbitrarily defined by setting an 80 km buffer to the mill with highest consumption in our study area, which is approximately 1000,000 tons year^{-1}. We then assigned the mills' consumption value to all pixels inside their buffers and summed the overlaying values to obtain the local roundwood consumption. Although transportation distances can be greater than 80 km for such mills under normal conditions (outside of a disturbed environment), our goal was to capture the effect of mills' size and respective levels of consumption in addition to their distance to forestlands.

Considering that ownership type may affect the decision of harvesting a damaged forestland, we included this categorical variable in our model, using the geospatial dataset compiled by Sass et al. (2020). Originally classified into eight types of properties, we aggregated these into three classes: Public (including federal, state, local, and tribal), Family (including family and other private - organizations, partnerships, and associations), and Corporate (including corporate and TIMO - Timber Investment Management Organizations / REIT - Real Estate Investment Trusts). Financial resources and owner's objectives are factors that can influence the willingness to proceed with salvage activities, leading to different harvesting rates between ownership classes. We used the Pearson's Chi-square test to evaluate if the rate of LCC (proportion between changed and unchanged land cover) varied significantly between ownership classes.

2.5. Machine learning models

To understand the main drivers of change in land cover classification of forest areas after a hurricane event, we tested a group of widely used machine learning models, assessing the effect of each explanatory variable, and comparing their performance in estimating forest land cover

Table 1
Description of the explanatory variables used in the machine learning models.

Theme	Explanatory Variable	Units	Data Source	Spatial Resolution
Hurricane characteristics	Maximum wind speed	km h^{-1}	NOAA/HURDAT2	250 m*
	Accumulated precipitation	mm	NASA/GPM	10 km
Forest structure	Stand age	Years	USDA/FS	30 m
	Basal area	m^2 ha^{-1}	USDA/FIA	30 m*
Market and operations	Terrain's slope	Degrees (°)	NASA/SRTM	90 m
	Distance to the nearest road	m	US Census Bureau	30 m*
	Distance to the nearest mill	km	Fastmarkets/RISI	30 m*
	Local roundwood consumption	Mt year^{-1}	Fastmarkets/RISI	30 m*
	Ownership type	Categorical	USDA/FS	30 m

* Raster data generated by authors using spatial data from the cited source.

change (LCC). Considered a binary dependent variable, LCC had only two possible outcomes: changed or unchanged forest land cover classification (1 or 0, respectively).

We tested the following machine learning models for binary classification: Logistic Regression Classifier, Decision Tree, Random Forest, K-Nearest Neighbor, XGBoost Classifier, CatBoost Classifier, Gradient Boosting Method (GBM), Light GBM, and Multilayer Perceptron These are widely used models, with a diverse range of applications with spatial data in forestry, land use/cover change, and landscape ecological studies (Estrada et al., 2023; Liu et al., 2020; Pichler and Hartig, 2023; Sebald et al., 2021; Sidumo et al., 2022; Stupariu et al., 2022; Zhai et al., 2020; Zhao et al., 2019), and showed satisfactory computational complexity (time and space demand) for the data under analysis. The values of the independent variables were standardized using Robust Scaler, a scaling method robust to extreme values (Pedregosa et al., 2011), and split into train and test sets, with 30 % of data assigned for testing.

We used the confusion matrix, in which observed and predicted values are compared, to calculate the performance measures of overall accuracy, precision, sensitivity, and the F1-score. While the first is a metric of overall performance, thus independent of class, the other 3 metrics focus on the minority class predictions. In this case, positive (P) and negative (N) refer to changed and unchanged land cover, respectively, while true (T) and false (F) indicate correct and incorrect classification. The precision metric denotes the proportion of true positives (TP) among all instances labeled as positive by the classifier. Sensitivity, also called recall, measures the proportion of TP results among all instances that belong to the positive class, indicating the model's capability to capture all positive instances without missing any. The F1-score is the weighted average of precision and sensitivity, with greater values indicating a higher classification performance. We compared the models mainly by their F1-score, but still evaluated the trade-off between precision and sensitivity, and used the overall accuracy as a complementary metric.

To evaluate the relevance of each explanatory variable for the model with best performance, we calculated their feature importance using the Gini-importance method, which represents the mean decrease in impurity obtained from splitting data on a given variable (Han et al., 2016), and the feature permutation method, which shows the decrease in a specific model's score (F1-score in this study) while repeatedly permutating values of a single feature (Altmann et al., 2010). Additionally, we calculated the one-way partial dependence to analyze the relationship between the predictors and their predicted response (Goldstein et al., 2014), in this case, the likelihood of change in the land cover classification. This method shows the marginal effect of a variable on the predicted outcome of the model, considering the average effect of all other variables. We performed this analysis using the test set (30 % of all data) due to computational limitations and showed the unscaled values of variables to facilitate the interpretation of results.

We used the libraries *Scikit-learn* (Pedregosa et al., 2011), *Imbalanced-learn* (Lemaitre et al., 2017), *XGBoost* (Chen and Guestrin, 2016), *CatBoost* (Dorogush et al., 2018), and *LightGBM* (Ke et al., 2017) to run the analyses in Python software. All models were tested using their default parameters, which are detailed in each provided library.

2.6. *Complementary data*

To broaden the scope of our analysis, we employed the same methods described for Hurricane Michael to evaluate the main predictors of LCC in three additional hurricanes: (1) Hurricane Laura, which made landfall in Louisiana on August 27, 2020, (2) Hurricane Florence, that struck North Carolina on September 14, 2018, and (3) Hurricane Hermine, that hit northwest Florida on September 2, 2016 (Fig. 2). Data availability and the presence of pine plantations in the hurricane's impact area were the main reasons for selecting these specific events. Laura was a "Category 4" hurricane, while the other two were classified as "Category 1" hurricanes at the time of landfall, being all less intense in terms of wind speed than Hurricane Michael ("Category 5").

3. Results

There is a substantial increase in the classification change from forest cover to other cover types immediately after Hurricane Michael's passage, with most changes being to classes "Cropland", "Grass/Shrub", and "Wetland" (Fig. 3). Of all pine plantations considered in the study area of Hurricane Michael (360,906 ha), we identified 28,396 ha that underwent a change in land cover classification from "tree cover" to "grass", "shrub," "crop," or "barren land" during the assessment period (first quarter after hurricane landfall).

The spatial distribution of the identified changes to forest cover is presented in maps, along with each explanatory variable used in the modeling approach (Fig. 4). Although, for visualization purposes, the maps may show data for the entire study area (e.g., for the wind speed and the precipitation variables) or for all forested areas (stand age and basal area maps), the predictive models tested in the following sections focused solely on the managed pine plantation area. A detailed map of LCC and the frequency distribution of explanatory variables are presented in the Appendix (Figures A.2 and A.3). Individual maps for each predictor with the identification of pine plantations and LCC are available as supplementary material (Figures S.1 to S.9).

In general terms, most changes to forest cover in the study area were observed close to the coast and to the hurricane's path, where forests were also subjected to higher wind speeds and precipitation volume. The terrain is relatively flat throughout the assessed region, with 90 % of the assessed forests being in a terrain with slope smaller than 5°. Basal area

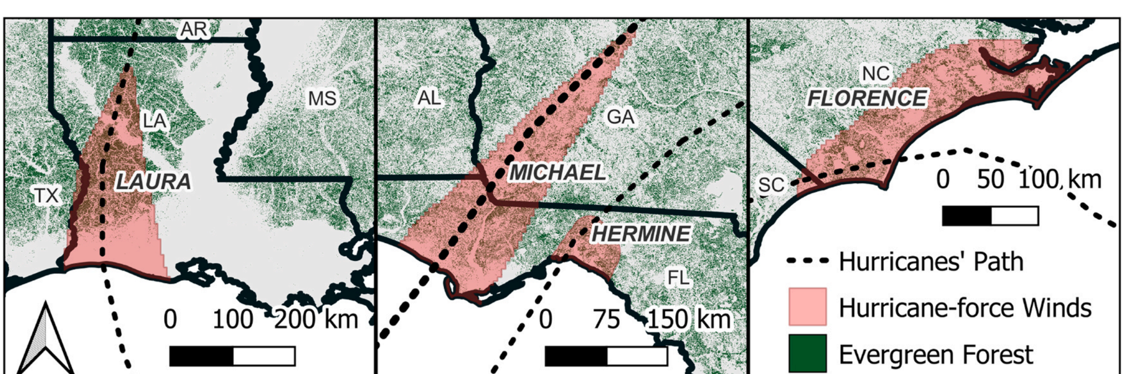

Fig. 2. Hurricanes' locations and trajectories, with areas potentially affected by hurricane-force winds (NOAA NHC, 2023). Forest cover data adapted from NLCD 2019 Land Cover (Dewitz and U.S. Geological Survey, 2021), showing exclusively the Evergreen Forest class (value 42). State abbreviations: AR (Arkansas), TX (Texas), LA (Louisiana), MS (Mississippi), AL (Alabama), GA (Georgia), FL (Florida), SC (South Carolina), NC (North Carolina).

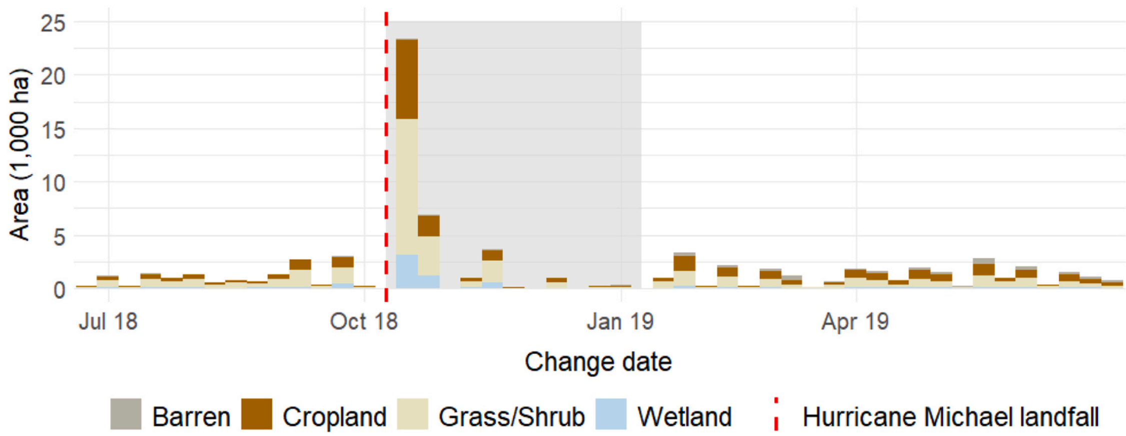

Fig. 3. Area and date of change in classification of forest cover to other land covers. Shaded area indicates the assessment period (first quarter after hurricane landfall).

has a heterogeneous spatial distribution, with some clusters of high-density forests. The mean basal area and age of pine plantations are 10 m^2 ha^{-1} and 32 years, respectively. There is a dense road network in the study area, with half of the assessed pine forests within 100–450 m from the nearest road, and a strong presence of roundwood-consuming mills, especially in Florida's portion. The majority (51 %) of the assessed forests are under corporate ownership, while public areas account for only 10 % of the total, primarily represented by the Apalachicola National Forest. In relative terms, family and corporate forests exhibited two and three times more changes in land cover classification, respectively, compared to public forests (Table 2), with these differences being statistically significant. This ranking is consistent with established research on harvest propensities by ownership group (Prestemon and Wear, 2000).

Regarding the data-preparation and sampling steps for the modeling approach, the number of observations in the training data exceeded the ones from the original set due to the use of SMOTENC as an oversampling technique, which generates artificial observations to reach data balance. The test set has the same distribution between LCC classes as the original data, with 30 % of its observations (Table 3).

The machine learning models were ranked based on their performance on the test set (Fig. 5), and the Random Forest model exhibited the best result, with a 65 % F1-score. The model could predict 70 % of all actual positive observations (LCC=1) and from all positive values predicted, 61 % were correct (true positive predictions). These values represent the model's sensitivity and precision, respectively. Some of the classification models, such as XGBoost, Multilayer Perceptron, and the Logistic Regression Classifier, reached high values of sensitivity, which is a desired metric when interested in the minority class of imbalanced datasets. However, these high sensitivity values come at the cost of losing precision, which will certainly lead to an overestimation of land cover change. The performance results achieved with the Random Forest model were considered satisfactory when dealing with such disproportional dataset. Although in different applications, models tested for datasets with similar imbalance also showed limited predictive power, with model performance degrading as the degree of class imbalance increases (Benkendorf et al., 2023; Graves et al., 2016; Meiyazhagan et al., 2022; Shin et al., 2021).

Our results were consistent between methodologies of feature importance calculation, showing similar trends in the ranking of variables (Fig. 6). For both methods, the maximum wind speed was the most relevant predictor of LCC for the Random Forest model. This variable was responsible for a 33.3 % mean decrease in impurity, and the random permutation of its values generated a decrease of 46.6 % on the F1-score. Distance to the nearest mill was the second most important feature, while the terrain's slope and ownership type had the lowest impact on the classification's performance.

The one-way partial dependence provides a visual representation of the strength and direction of the relationship between the likelihood of change in the land cover classification and the predictors of such change (Fig. 7). An increasing effect is observed for the maximum wind speed, stand age, basal area, and pine consumption, with the first being the most impactful variable in the prediction outcome and showing the most accentuated marginal effect. The probability of change increased almost linearly starting at windspeeds above 100 km h^{-1}. Contrarily, the distance to the nearest mill had a decreasing effect for values ranging from 0 to 30 km, which corresponds to around 75 % its distribution, meaning that longer distances inside this range resulted in a lower probability of change. Though considered an important predictor for the classification model, there was no explicit trend for the effect of precipitation when assessing it individually. The distance to the nearest road showed higher impact in the likelihood of change for values inferior to 200 m (around 45 % of observations), with low and constant impact for greater distances. In agreement with the feature importance results, changes in terrain's slope had minimal impact in the model.

In a broader analysis, we observed that the importance of each explanatory variable varied when predicting the changes to forest cover classification for different hurricanes (Fig. 8). For instance, the maximum wind speed was not as individually important for the other hurricanes as it was for Hurricane Michael. Although this feature of storm intensity remained classified as a main predictor of LCC, other variables were found to have similar importance, such as the distance to the nearest mill, basal area, and total precipitation. For Hurricane Laura, pine consumption also emerged as a relevant predictor (39 % mean decrease in the model's F1 score), showing three times the importance of the stand's age (13 %). The ownership type and terrain's slope were identified as low-importance predictors in all cases.

4. Discussion

Our results indicate a close link between the passage of Hurricane Michael and the observed changes in land cover classification within the impacted forest region. However, despite a noticeable increase in these changes immediately after the hurricane's landfall (Fig. 3), it is essential to note that they constitute only a relatively small fraction (less than 5 %) of the overall damaged forest area, which exceeds 1000,000 ha of pine forests according to post-disturbance estimates.

As previously described, the CCDC algorithm employed in LCMAP detects "breaks" in a time series model when multiple clear consecutive observations from satellite imagery substantially differ from predictions (Zhu et al., 2020; Zhu and Woodcock, 2014). Originally designed to monitor abrupt changes, this algorithm has shown limitations in

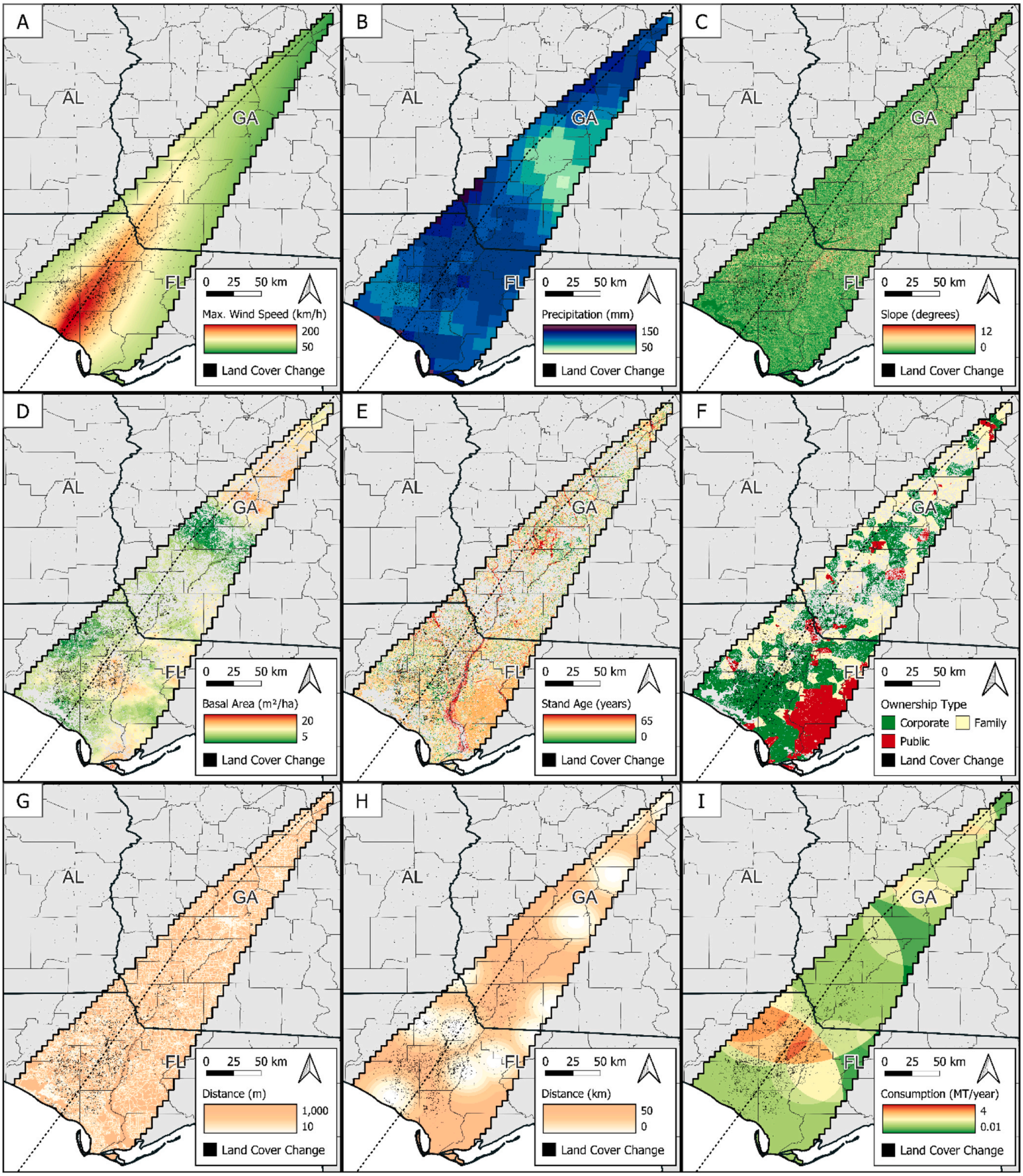

Fig. 4. Spatial distribution of explanatory variables and land cover change. A: Maximum wind speed (km h^{-1}), B: Total precipitation (mm), C: Terrain's slope (°), D: Basal area (m^2 ha^{-1}), E: Stand age (years), F: Ownership type, G: Distance to nearest road (m), H: Distance to nearest mill (km), I: Pine consumption (1000,000 tons $year^{-1}$). Dashed line indicates the path of Hurricane Michael.

detecting gradual transitions in land cover (Brown et al., 2020). Therefore, due to its primary capability in detecting abrupt land surface changes, we anticipate that shifts in land cover observed in forested areas following storm disturbances reflect severe damage scenarios, characterized by significant reductions in tree cover. Additionally, in some cases, these observations may also capture modifications to land cover associated with harvesting activities and the removal of timber material.

This study aimed to establish a potential link between salvage logging and post-hurricane shifts in forest cover classification by assessing

Table 2
Ownership types of managed pine plantations inside the study area and respective changes in land cover classification.

Ownership		LCC		Area (ha)
Type	%	Type	%	
Corporate	51 %	0	90 %	165,170
		1	10 %	18,759
Family	39 %	0	94 %	132,859
		1	6 %	8488
Public	10 %	0	97 %	34,481
		1	3 %	1148

LCC: Land cover change, with types 0 and 1 representing unchanged and changed land cover classification, respectively.

Table 3
Data distribution by land cover change (LCC) classes for the original and the training data.

LCC	Original data		Training data*	
	Number of observations**	%	Number of observations**	%
0	3694,560	92.13 %	2586,242	50.28 %
1	315,512	7.87 %	2557,462	49.72 %
Total	4010,072	100 %	5143,704	100 %

* Resampled using SMOTENC and Tomek Links.
** Satellite image pixels with 30 m resolution.

the primary predictors of these changes. While the results indicated variability in the main factors influencing these changes across different events, certain variables consistently emerged as significant in all tested models (Fig. 8). Beyond the expected storm-related factors associated with damage severity, like maximum wind speed and precipitation (Feng et al., 2021; Fortuin et al., 2023; Hall et al., 2020), we identified forest and market/operations attributes as important predictors of changes. The relevant forest-related variables, stand age and basal area, could influence both damage levels and salvage site selection since they relate to forest's vulnerability to storm events (Beach et al., 2010; Gardiner, 2021; Kupfer et al., 2008; Oswalt and Oswalt, 2008; Taylor et al., 2019) and to the monetary value of trees. However, the importance of a market/operational variable, in this case the distance between a forested area and the nearest mill, should not be associated to the spatial pattern of severity as it does not influence how susceptible forest ecosystems are to hurricane disturbances.

The distance to the nearest mill was among the top three predictors for all the assessed hurricanes, holding an average importance of 42 %, as indicated by the decrease in the model's F1-score using the feature permutation method. Furthermore, the partial dependence analysis revealed that for 75 % of observations the likelihood of change to a non-forest cover decreased as the distance to mill increased (Fig. 7). This observed trend aligns with expectations for salvage site selection, indicating a preference for harvest locations closer to mills. This preference is driven by the aim to minimize transportation costs, particularly in scenarios characterized by low timber prices. Research suggests that hauling activities constitute 20–35 % of total forestry operational expenses in southern US and frequently operate at a negative margin, notably when handling low-value products like pulpwood (Audy et al., 2023; Conrad, 2021; Grebner et al., 2005).

We expected that the distance to the nearest road would reflect some operational constraints, such as accessibility restrictions of damaged stands and the costs of salvaging timber deep into larger forested areas (Conrad, 2023), thus showing relevance in the models. However, the below-average importance of this variable was highlighted only for extremely short distances (lower than 150 m). This result may relate to the greater wind exposure and consequent vulnerability of trees close to stand edges (Beach et al., 2010; Gardiner, 2021) and cannot be attributed exclusively to salvage operations.

The partial dependence analysis for Hurricane Michael revealed a

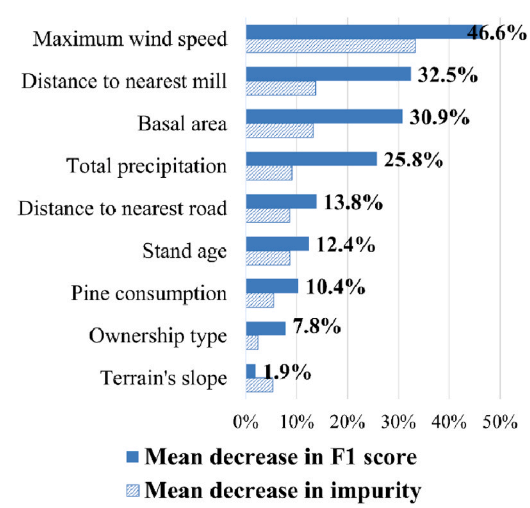

Fig. 6. Feature importance results for the Random Forest classification model fitted on Hurricane Michael data, ranked by the mean decrease in the F1-score.

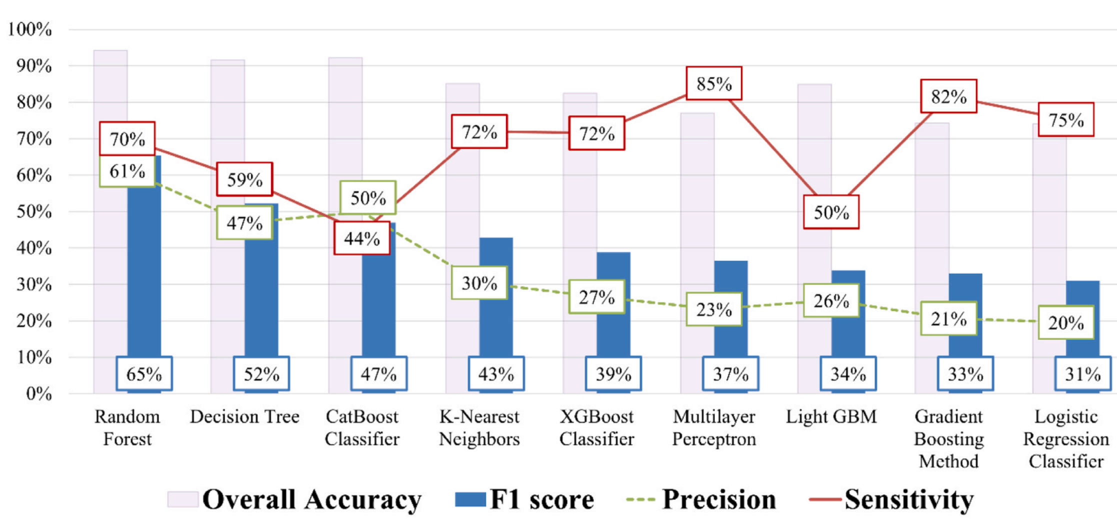

Fig. 5. Performance metrics of the classification models on the test set of Hurricane Michael, ranked by the F1-score.

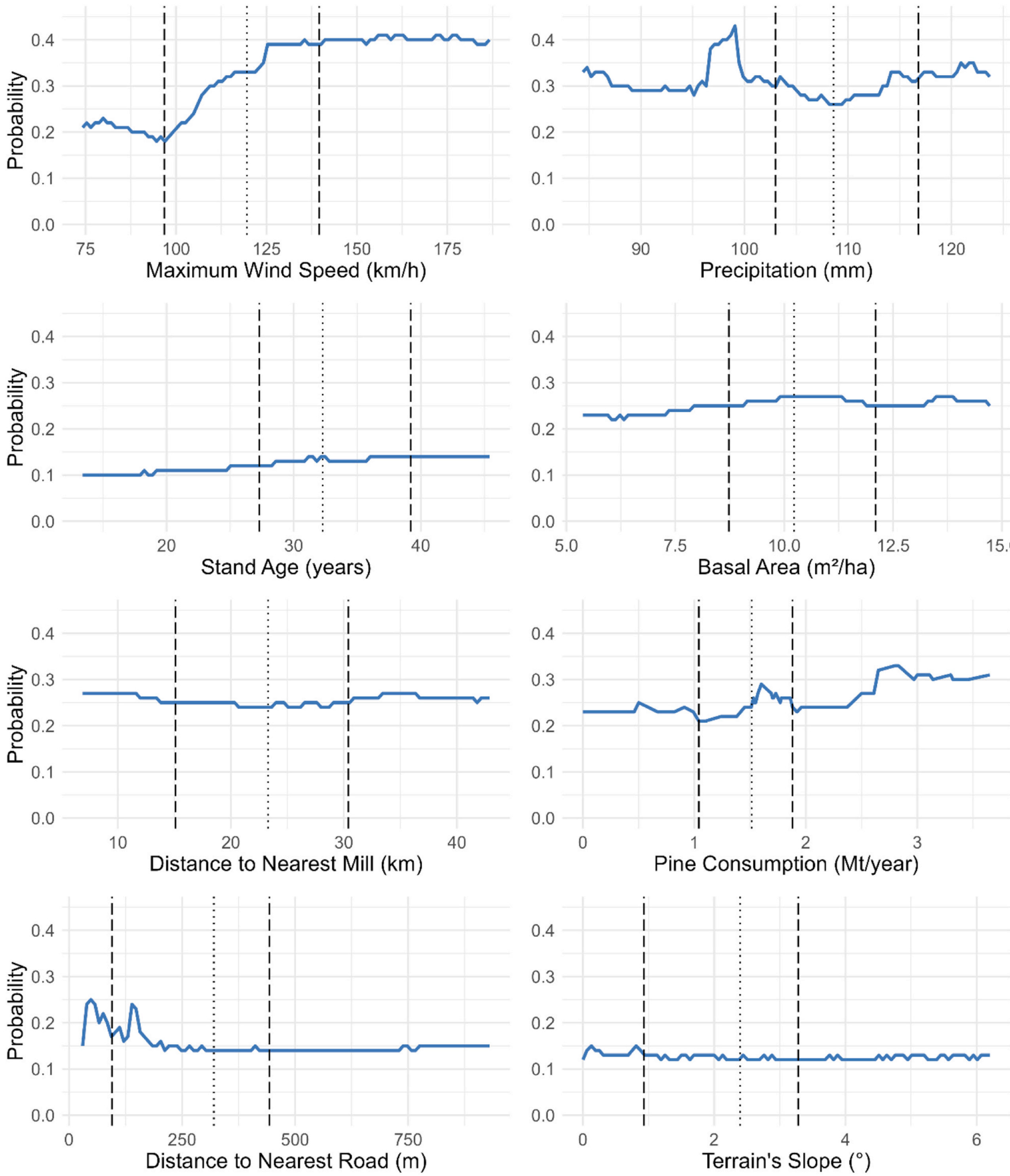

Fig. 7. One-way partial dependence for the continuous predictors of the Random Forest classification model, fitted on Hurricane Michael data. The dotted lines represent mean values, while the dashed lines represent the first and third quartiles of the corresponding predictor variable distribution.

positive correlation between pine consumption and the likelihood of land cover change (Fig. 7), aligning with our earlier findings on the distance to mill variable and market expectations. Intriguingly, despite this alignment, the pine consumption variable was not identified as a primary predictor of these changes. Some characteristics of the data offer possible explanations for this result: (1) the pine consumption and distance to mill variables are the ones with higher correlation (-0.32), which is strengthened (-0.42) after employing the scaling and sampling techniques (Figure A.4); (2) the high consumption values (above 2.6 Mt) with increased impact on prediction outcomes represent only 12 % of observations; and (3) the different behavior of its marginal effects observed for certain ranges of consumption values may reflect possible interactions with other variables. As an effort to avoid redundancy of predictors and improve models' performance, we tested the random forest model using the two correlated variables separately and as a single combined predictor. The importance of each individual variable was obviously highlighted. However, these models showed a lower performance, with F1-scores below 60 %. The varying results for pine

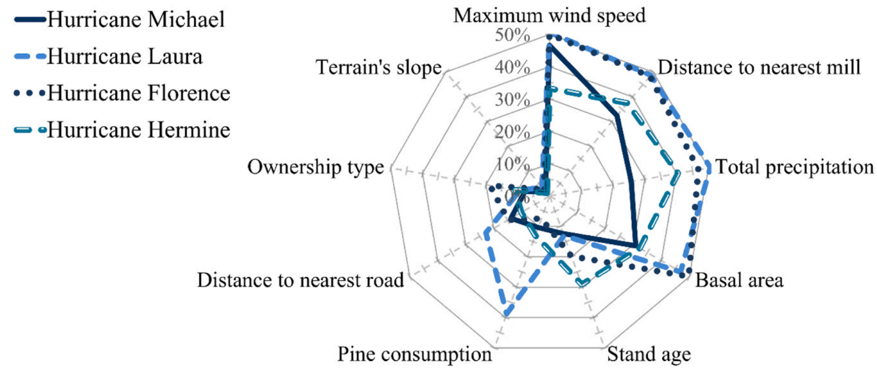

Fig. 8. Comparison of the permutation-based feature importance between different hurricane events, calculated for the Random Forest classification model. Concentric circles represent the mean decrease in the F1-score. Variables ranked clockwise based on their average importance.

consumption, especially the exceptional importance observed for Hurricane Laura, are likely related to particularities of each study area, such as the mills' size and their spatial distribution in relation to the forest damage area and severity.

The rates of change in land cover classification varied significantly between ownership types, with corporate-owned pine plantations experiencing more changes when compared to others (Table 2). Considering the low influence of this aspect over potential storm damage, this observation may be connected to the different rates in salvage logging activities. Corporate owners tend to respond more quickly and intensively after a hurricane, which could be attributed to their specific objectives and greater financial resources. Additionally, corporate owners often have fiber supply agreements with wood-consuming mills, granting them increased access to salvage opportunities (Georgia Forestry Commission, 2012). On the other hand, logging capacity, budget limitations, or non-profit-maximization objectives may hinder timber salvage in family-owned properties (Beach et al., 2010) and can help to explain the lower rates observed compared to the corporate ownership class. The administrative procedures required to harvest in public lands may also contribute to the lower rates of land cover change in these areas, implying minimal to no salvage activities in the short term (Bruck and Frey, 2023). Despite these observations, the ownership type did not emerge as an important feature in the binary classification process of the Random Forest model, regardless of the hurricane. This may be attributed to a limitation of the model in effectively handling categorical variables, especially with a small number of categories (Altmann et al., 2010).

Although the terrain's slope may influence forest vulnerability to storm damage and was previously identified affecting damage severity in a similar region and disturbance event (Wang and Xu, 2009), we included this variable in LCC prediction because of its potential influence on harvest site selection. Since slope is already a limitation for harvesting under regular conditions (Germain et al., 2019; Lahrsen et al., 2022), we expected steeper damaged areas to be completely abandoned during salvage efforts, therefore leading to some impact of this variable over the predictions' outcome, considering LCC could represent salvage activity. The relatively low steepness of terrain within the study area, particularly for the pine plantation area, is most likely the explanation for its minimal impact on model's performance.

The proposed methodology was limited to identifying large modifications in land cover due to the spatial resolution of data sources. Therefore, it does not account for partial cutting, which is a significant share of the salvaged timber volume (Brandeis et al., 2022). The use of satellite imagery of finer resolution, multitemporal analysis with proper vegetation indices (Jin and Sader, 2005; Lastovicka et al., 2020), or the evaluation of changes in forest density, such as basal area losses (Lu et al., 2022; St. Peter et al., 2020), could be possible solutions to incorporate all the harvesting that has taken place.

To deepen the understanding of hurricanes' post-disaster management dynamics and improve the applicability of our results, new research could focus on refining LCC patterns, currently assessed at an individual pixel level, distinguishing disturbance agents, identifying alternative relevant predictors, and enhancing machine learning models application, especially for working with imbalanced datasets.

Exploring the use of neighborhood analyses to smooth predictions within contiguous forested areas (e.g., Koistinen et al., 2008; Shive et al., 2018) offers a promising approach to defining clearer patterns of forest cover change. Complementary, the evaluation of common patch metrics of natural and anthropogenic disturbances, including their size and geometry, not only aids in this endeavor but also supports the attribution of causal agents of disturbance (Schroeder et al., 2017; Sebald et al., 2021; Senf and Seidl, 2021). In this direction, distinguishing thematic land cover changes between storm damage and salvage activity presents another potential avenue for enhancing research outcomes, leading to more accurate data and the development of better predictive models. Incorporating additional variables derived from satellite imagery, such as remotely sensed vegetation indexes and their levels of change during specific time frames (W. Wang et al., 2010), could further facilitate the segregation of disturbance causes.

Efforts in the realm of machine learning models could focus on leveraging advanced methods for finer hyperparameter tuning, alongside the implementation of spatial cross-validation techniques. These methods try to ensure that models show their best possible performance on the dataset (Probst et al., 2019; Schratz et al., 2019) and have generalization power, avoiding overoptimistic performance estimates when dealing with large spatial datasets (Meyer et al., 2019). Incorporating spatial cross-validation becomes especially crucial in the presence of spatial autocorrelation, as it helps understand how nearby areas may influence each other and ensures robust model evaluation across spatial dimensions (Sebald et al., 2021). For instance, predictors used in mapping or attributing causal agents of LCC may vary in importance across spatial blocks, necessitating careful validation strategies to mitigate potential biases in model results. Ultimately, addressing the data imbalance problem is critical, given the significant disproportionality between classes observed in this study - where only 7.87 % of the forested area experiences a change in land cover classification. In such scenarios, observations in the minority class can be considered "rare events," and models often exhibit limited performance in predicting them, particularly as the degree of class imbalance increases (Meiyazhagan et al., 2022; Shin et al., 2021). Therefore, exploring alternative approaches to tackle this issue is imperative for enhancing the effectiveness and reliability of predictive models in this context.

5. Conclusion

The purpose of this study was to evaluate a possible connection between salvage logging and the changes in land cover classification within forested regions following a hurricane. We tested machine learning models and assessed their performance in predicting land cover changes, using features associated to hurricane characteristics, forest structure, and market/operations aspects as predictors of these models. We focused on exploring the importance and the relationship of individual variables in the predictive power of these models. The results of our examination, which include the total area under modification, the feature importance within predictive modeling, and the variables' effects over the likelihood of change, leads us to infer that the observed modifications in land cover extend beyond the direct impact of the storm on forests. Instead, these thematic changes likely represent an additional transformation in land cover induced by the removal of damaged timber material, thus serving as a proxy for salvage logging activities.

CRediT authorship contribution statement

Ian Pereira Sartorio: Writing – original draft, Visualization, Formal analysis, Conceptualization. **Bruno Kanieski da Silva:** Writing – review & editing, Conceptualization. **Jesse D. Henderson:** Writing – review & editing, Conceptualization. **Mohammad Marufuzzaman:** Writing – review & editing. **Michael K. Crosby:** Writing – review & editing. **Shaun M. Tanger:** Writing – review & editing, Conceptualization.

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

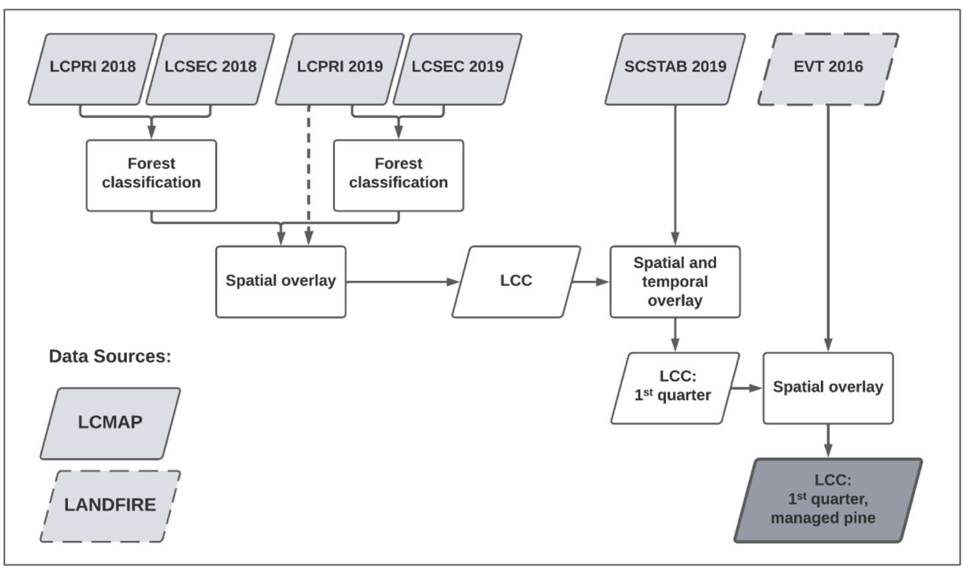

Figure A.1. Flowchart of data and processes used to calculate the change in forest area between 2018 and 2019. LCPRI: primary land cover, LCSEC: secondary land cover, SCSTAB: spectral stability period, EVT: existing vegetation type, LCC: land cover change, LCMAP: Land Change Monitoring, Assessment, and Projection (USGS, 2021), LANDFIRE: Landscape Fire and Resource Management Planning Tools (LANDFIRE, 2020). Adapted from Dwomoh et al. (2021).

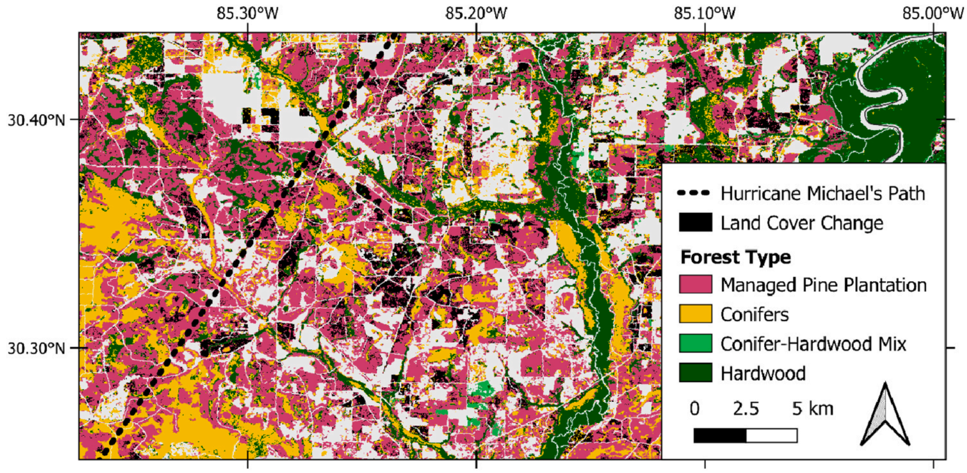

Figure A.2. Detail in larger scale of the study area, highlighting the land cover change (LCC), managed pine plantations, and other forest types. The study's analyses were restricted to the pine plantation area, including the identification of LCC. Forest type classification was adapted from LANDFIRE (2020).

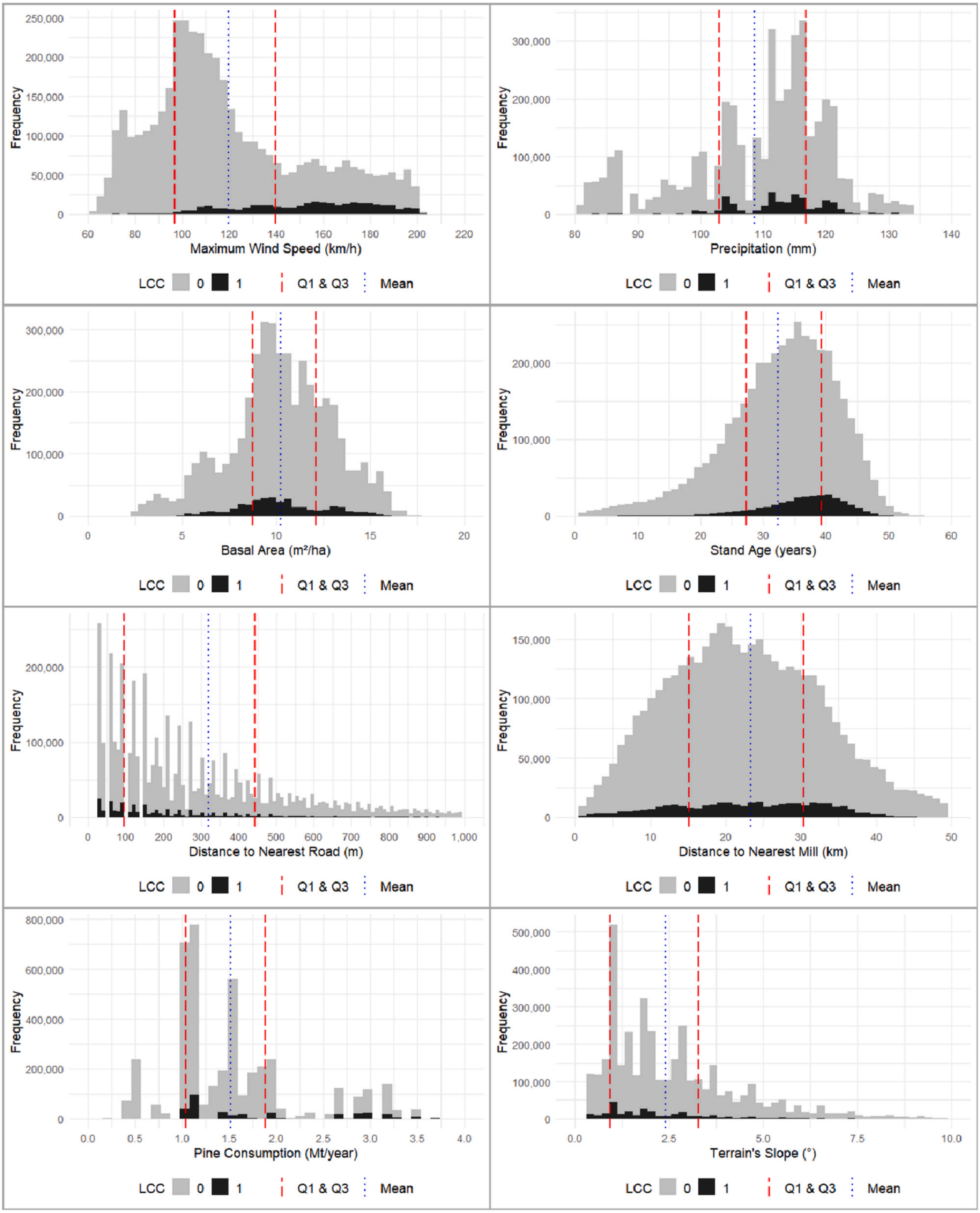

Figure A.3. Frequency distribution of continuous explanatory variables, exclusively for managed pine plantations, segregated by Land Cover Change (LCC). Definitions: LCC=0, unchanged land cover classification; LCC=1, changed land cover classification; Q1 & Q3, first and third quartile.

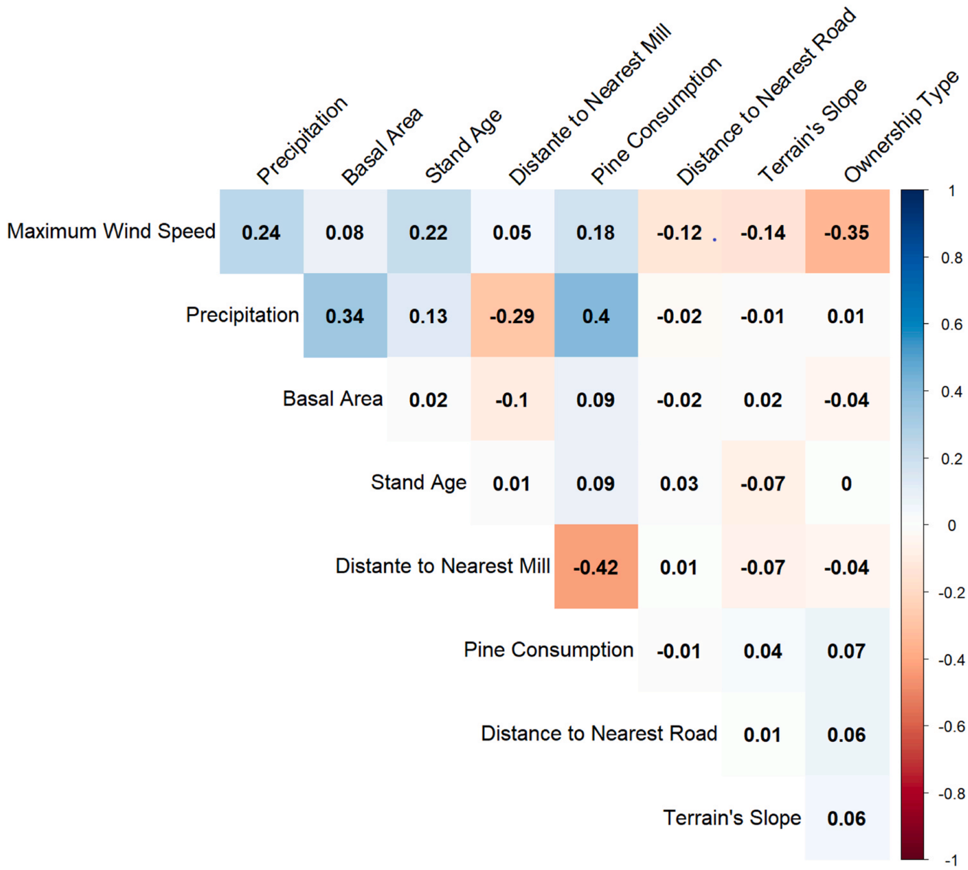

Figure A.4. Correlation matrix of explanatory variables after employing scaling and sampling techniques. Correlations were significant at *p*-values <0.05.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.foreco.2024.122132.

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