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Harvesting wind damaged trees: a study of prediction of windthrow damage in mixed-broadleaf stands via a machine learning model

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ABSTRACT

Due to climate change, windstorms are becoming increasingly common resulting in the destruction not only of extensive forest areas but, quite often, of small-sized and scattered forest lands, thereby adversely affecting both the productivity and the safety of workers employed in the harvest of windblown trees. In the present study, an attempt is made to identify and record areas in the northeastern forests of Greece covered by mixed stands of conifers and broadleaves that experienced massive windthrow following local storms. Our results reveal that where *Pinus sylvestris* was mixed either with *Quercus sp.* or with *Fagus sylvatica*, it had been substantially protected, while in plots where it stood on its own it had been extensively uprooted. On the other hand, *Picea abies*, even if it was mixed with *Fagus sylvatica* and *Pinus sylvestris*, had been blown down to a large extent. Based on tree-level data, local topographic features, forest characteristics, and the mechanical properties of green wood, a reliable model, to be used for the prediction of similar disturbances in the future, has been selected after a thorough comparative study of the most well-known intelligent Machine Learning (ML) algorithms. Specifically, Random Forest Classifier, k-Neighbors Classifier, Decision Tree Classifier, Light Gradient Boosting Machine, Gradient Boosting Classifier, Ada Boost Classifier, Ridge Classifier, Linear Discriminant Analysis, Logistic Regression, Naive Bayes, SVM – Linear Kernel, and Quadratic Discriminant Analysis were evaluated and compared using six performance measures (confusion matrix, accuracy, precision, recall, F1-score, and ROC).

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Introduction

Over the last years, windthrow has become an increasingly significant factor of natural disturbance. In recent decades, Europe has been hit by a series of severe storms. One such example is Cyclone Niklas, which, in March 2015, caused extensive damage to the forests of southern Germany, with the mountains of Zugspitze (where hurricane force winds reached 192 km/h), Brocken (162 km/h), Feldberg in the Black Forest (151 km/h), and Weinbiet Neustadt (148 km/h) bearing the brunt of the storm (German Weather Service, DWD). Severe storms are, unfortunately, predicted to become even more frequent in Europe as a result of climate change (Schelhaas et al. 2003; Seidl et al. 2014).

Research on the impact of windstorms on temperate forests has generally focused on catastrophic disturbances related to the most severe winds (Dunn et al. 1983; Foster 1988; Peterson and Pickett 1991; Cooper-Ellis et al. 1999; Canham et al. 2001). The range of disruptions they bring to the forest vegetation is an important parameter affecting in the long run the composition and structure of ecological systems in general (Pickett and White 1985; Canham et al. 2001).

It is important to note that natural disasters (windthrow incidents included) lead to exceptionally harsh logging conditions, particularly when timber is scattered over large areas due to severe winds (Oprea and Sbera 2004). What is more, when harvest areas are not easily accessible, salvage logging conditions become even more difficult due to the increased production costs (related to smaller productivities) and depreciation of the harvested timber (Nieuwenhuis and Fitzpatrick 2002).

Other salvage logging related problems include health and safety issues, as the occupational safety of workers dealing with scattered windthrown timber is considerably reduced in comparison with those employed in regular cuttings (Borz 2013). More specifically, the most hazardous operations that loggers perform include tree felling, clearing the area surrounding the tree to be felled and clearing a path to the tree to be felled. Moreover, choker setters are exposed to increased hazards in comparison with their peers working under normal conditions (Sullman and Kirk 2001).

Uprooting (windthrow) and breakage of the tree trunk (windsnap) may cause local disturbance to the soil, as well as the formation of canopy gaps; the latter triggers the generation of early successional broadleaved species (Jankowska-Blaszcuk

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and Grubb 2006). According to Böhm (1981), the composition and ratio of autochthonous to non-autochthonous species are altered, a fact that would entail a shift from deciduous trees to unstable conifers such as spruce (Schelhaas et al. 2003).

The short-term consequences of these disturbances include the damage incurred by the resulting insect communities, mainly the European spruce beetle [*Ips typographus* (L.)], thriving in the affected trees. More generally in Europe, both abiotic factors (windthrow) and biotic (bark beetle infestations) are serious causes of disturbance (Seidl et al. 2014).

In a period of 50 years (1950–2000) the average annual damage to wood from storms in Europe amounted to 18.7 million m^3, with most windthrow damage taking place in Central Europe and the Alps. For the same period, short-term wood damage from insect attacks amounted to 2.9 million m^3 per year (Schelhaas et al. 2003). Taking the above into consideration, it becomes clear that windthrow forest areas must be identified as soon as possible in order to reduce the impact of the resulting biotic disturbance, as damaged trees yield substantial material for insect reproduction (Schelhaas et al. 2003; Seidl et al. 2014). More generally, delineating windthrow areas is deemed crucial both for the calculation of the damaged wood volume and in order to effectively schedule and plan the processing and marketing of the damaged wood to prevent its further degradation (Koloman 2013).

Identifying damaged sites and determining the extent of a wind disaster by means of terrestrial methods is often problematic, especially in the case of multiple and smaller-sized mosaic-like disturbed areas. For this reason, measurements conducted with the use of global navigation satellite systems (GNSS) are the most common for this task (Tomaštík 2016). Data collection can also be performed using unmanned aircraft systems (UAS), a remote sensing technique that can provide accurate and detailed data (Tang 2015). UASs have also been employed in a number of studies focusing on forest disturbance incidents, such as fires (Yuan 2015) and insect infestations as well as the detection of smaller areas whose size is below 0.5 ha. (Honkavaara et al. 2013; Duan et al. 2017). As an alternative to UAS imagery, images obtained from the Pléiades satellite could be used (Vaudour et al. 2017) but are more expensive for small-sized areas.

Based on tree-level data, local topographic features, forest characteristics, and the mechanical properties of green wood, this paper proposes a reliable machine learning (ML) methodology that can be used to analyze windthrow damage in mixed-broadleaf stands and predict similar disturbances in the future. Specifically, to prove the generalization ability of the proposed classification approach, we used a dataset comprising 455 windthrow damage cases. In order to develop the ML model, eight features (location, species, area, broken area, broken height, gradient %, aspect) and a class (uproot or not) were used. Validation performance reports the average accuracy computed over 10-fold cross-validation in the classification process described below.

ML is a branch of artificial intelligence and computer science that trains computers to learn from data without being explicitly programmed. It is a sort of data mining that helps computers "learn" by studying data sets and recognizing patterns. ML has several advantages in forest engineering, including increased accuracy and efficiency, as well as improved decision-making.

Furthermore, ML addresses a variety of difficulties, including:

(1) Handling vast volumes of data: With the ever-increasing amounts of data created by forest applications and monitoring processes, forest engineers find it increasingly challenging to interpret and make sense of all this information. ML may assist forest management and civil protection organizations in handling enormous volumes of data more efficiently and effectively, and it can even facilitate optimal decisions for action in the forest environment.
(2) Reducing bias: Unlike humans, ML algorithms are not prejudiced toward certain data sets, which might affect their judgment. As a result, ML can assist in the reduction of bias in forest management decisions, especially in damage prediction.
(3) Improving accuracy: When making damage predictions or categorizing damage data, ML algorithms may achieve significantly greater accuracy than humans or the other more traditional methodologies. This enhanced precision can lead to better outcomes and more efficient environmental management programs.
(4) Identifying hidden patterns and correlations: ML may assist forest management organizations in identifying patterns and correlations in data that they may not have detected otherwise. These learning systems have the potential to improve decision-making and provide a more profound comprehension of facts.
(5) Making future event predictions: ML algorithms can forecast future events such as damage prediction, windthrow behavior in specific local areas, etc. This can assist forest organizations and civil protection authorities in planning for the future and capitalizing on emerging possibilities.

The present study is part of a broader, long-term research effort whose objective is to spatially assess the climate change experienced by Greece due to its geophysical location and diverse climate. Its aim is twofold: on the one hand, the investigation and understanding of the role local topographic agents play in windthrow events, in combination with the characteristics and mechanical properties of green wood species that experience windthrow damage; on the other, the creation of an ML model (Liski et al. 2020) which, once trained over the real data collected, will be capable of carrying out accurate predictions (Lopes et al. 2022) of future windthrow disasters under similar environmental and topographic conditions and with similar mechanical tree characteristics.

Materials and methods

In April 2020, for three consecutive days (5 to 7 April), moderate to strong winds developed in locations northeast of the Rodopi Mountains, Northern Greece. On April 5, maximum wind gusts reached 187.5 km/h, and in the next 2 days, maximum gusts of 140.79 km/h and 155.23 km/h, respectively, were recorded (www.wunderground.com). The main area that was hit is located to the NE of the City of Xanthi. The strong winds caused a heterogeneous damage pattern including uprooting and trunk breakage mainly in small-sized mosaic-type sites. Salvage logging included motor-manual felling by means of chainsaws and skidding with the use of tractors (highly mechanized harvesting system).

After the storm event, and in order to assess the extent of the damage and identify the storm-hit areas, an unmanned aircraft system (Parrot Anafi) was used to scan an area of approximately 159 ha. Of the total of locations that were UAS-scanned, four sites were found to have been severely battered. These sites belonged to four mixed stands consisting of conifers and broadleaves located NE of the City of Xanthi.

The names we assigned to the plots are based on the items damaged in each plot. More specifically, in stand 27a (PsMxQu) (Table 1), where *Pinus sylvestris* trees occurred in mixtures with *Quercus sp*. (with neither of the two species being dominant), it was found that a specific plot, hereinafter referred to as "plot aPISY," was seriously affected. In stand 26c (PsDomxQu), also made up of a mixed *Pinus sylvestris* and *Quercus sp*. community, the former being the dominant species, the corresponding damaged section was assigned the name "plot bPISY." In both aPISY and bPISY plots, the damaged species was *Pinus sylvestris*. In the third stand, stand 7a (FsDomxPs), consisting of a mixed *Fagus sylvatica* and *Pinus sylvestris* assemblage, with *Fagus sylvatica* being the dominant species, the damaged location was named "plot aPIAB." Finally, in the fourth stand, stand 7b (PsDomxFs), also consisting of mixed *Pinus sylvestris* and *Fagus sylvatica* trees, with *Pinus sylvestris* being the dominant species, the damaged site was named "plot bPIAB" (Figure 1). In plots aPIAB and bPIAB, the damaged species was *Picea abies*.

To put it in a nutshell, the four stands were all mixed communities of conifers and broadleaves, in two of which (26c and 7b) conifers were the prevailing species, one (7a) was dominated by broadleaves, whereas in the fourth (27a) there was no dominant species. Plots aPISY and bPISY were composed solely of *Pinus sylvestris*, whereas the other two plots, aPIAB and bPIAB, were occupied by mixtures of *Pinus sylvestris* and *Fagus sylvatica* and also a number of *Picea abies* individuals as a secondary species.

After identifying the four windthrow plots, a series of field measurements were carried out. These included a) the totality of the damaged trees in all four locations, which were subsequently classified according to forestry species and type of damage per plot. It must be clarified here that in the current study, we took into account only the uprooted trees and not the broken ones; b) the diameter at breast height of the uprooted trees; and c) with the help of Garmin Dakota 20 GPS, the area, elevation, as well as the aspect of each affected plot.

In order to draw conclusions pertaining to the properties of green wood and the strength and resilience of the species that were affected (*Pinus sylvestris* and *Picea abies*) as well as of those which were within the windthrow stands but did not experience any damage (*Fagus sylvatica* and *Quercus sp*.), the Stuttgart Table of Wood Strength (Wessolly and Erb 1998) was taken into account for the species concerned. This list (Table 2) refers to the mechanical properties of green wood (i.e., standing wood) and not of wood in use.

Table 1. Summary of the windthrow areas (stands and plots).

Name	Designation	Dominant species	Secondary species	Name of plot	Stand area (Ha)	Wood volume m^3
(27a) Conifer–hardwood mixed species	PsMxQu			aPISY	36.36	4987
(26c) Conifer–hardwood mixed species	PsDomxQu	Ps dominated		bPISY	38.23	5496
(7a) Hardwood–conifer mixed species	FsDomxPs	Fs dominated	*Picea abies+ Prunus+Betula+Populus*	aPIAB	41.42	16,198
(7b) Conifer–hardwood mixed species	PsDomxFs	Ps dominated	*Picea abies+ Prunus+Betula+Populus*	bPIAB	42.98	15,275
Sum					158.99	

Ps = *Pinus sylvestris*, Fs = *Fagus sylvatica*

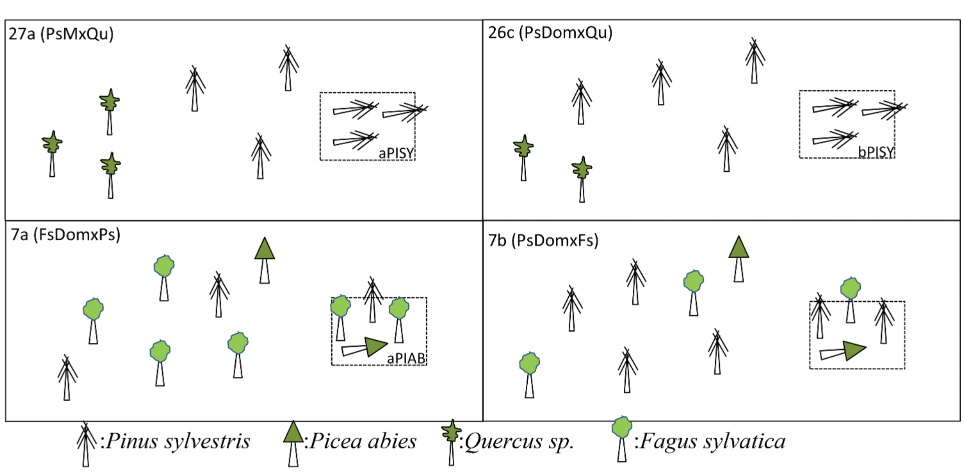

Figure 1. Schematic representation of the plots.

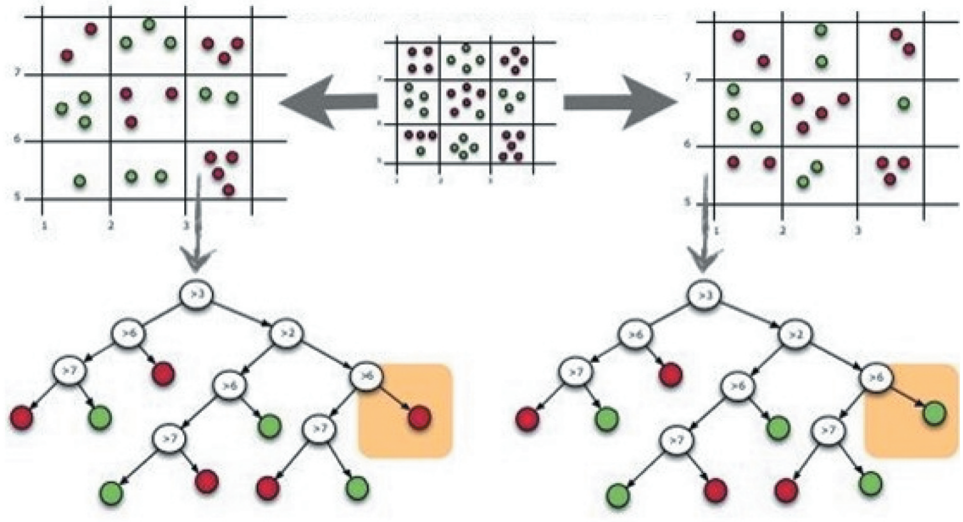

Figure 2. Operation of random forest.

Table 2. Stuttgart table of wood strength (Wessolly and Erb 1998).

Species	Modulus of elasticity (N/mm^2)	Comparable strength in longitude (N/mm^2)	Elastic limit (%)	Proposed aerodynamic drag factor (c_w)
Pinus sylvestris	5800	17.0	0.29	0.15
Picea abies	9000	21.0	0.23	0.20
Fagus sylvatica	8500	22.5	0.26	0.25–0.30
Quercus robur	6900	28.0	0.41	0.25

Intelligent data analysis

In order to create a forecasting model for the prediction of storm disasters based on tree-level data, a comprehensive comparative study of the most well-known machine learning algorithms was carried out. Machine learning is one of the most important and most widely used fields of artificial intelligence that includes data-driven computational methods (Usui 2021) for studying and building algorithms (Keefe et al. 2019) that can learn from appropriate data (Strange et al. 2021) and, based on this experience, carry out accurate future forecasts (Starke and Geiger 2022).

In recent years, machine learning has been used in various environmental issues, such as the exploration of the impact of climate change on biodiversity (Demertzis and Iliadis 2018), the modeling of forest fires (Anezakis et al. 2018), the analysis of exhaust emissions generated by chainsaws (Dimou et al. 2018), and the prediction of interior spruce wood density utilizing progeny test information (Demertzis et al. 2017).

The concept of *experience* mentioned above refers to the hidden knowledge included in the field data we collected, which are related to local topographic factors, forestry characteristics as well as the mechanical properties of species in association with the type of damage they suffered. To be more specific, we used as independent variables the characteristics related to the topographic area, the size of the damaged sites, the forestry species, diameter at breast height, slope, and geographic orientation. The only dependent variable that we used was whether the tree was uprooted or not. Consequently, we came up with a binary classification problem (Bahel et al. 2020).

Binary classification concerns the grouping of each sample into one of the two predetermined classes. The term "training" of a machine learning model by means of the classification method refers to the process that calculates the equation $\hat{f} : R^N \to T$, where T is a set of labels that indicate the class (whether the tree was uprooted or not). In this problem, we considered as a key evaluation metric the error corresponding to an incorrect prediction, which depends on the concept of relative distance between the different classes (Canbek et al. 2017).

An extensive comparison of the most widely used supervised ML models was made to identify the most effective classification algorithm. A comprehensive review of the models considered is summarized as follows:

(1) **Random Forest Classifier**: A Random Forest (as depicted in Figure 2) is a meta-learner that creates several categorizing decision trees on different sub-samples of the dataset and utilizes averaging to increase predicted accuracy and control over-fitting (Breiman 2001).
(2) ***k*-Neighbors Classifier**: *k*-Nearest Neighbors are a similarity-based learning technique that predicts the target by locally interpolating the targets associated with the training set's nearest neighbors (Bremner et al. 2005).
(3) **Decision Tree Classifier**: A decision tree-based model that presents conditional control statements by integrating random event outcomes and resource costs.

The pathways represent the classification process from the root to the leaf. Each node represents an attribute, each branch represents the result of an attribute test, and each leaf reflects the decision made once all details have been computed (Kamiński et al. 2017).

(4) **Light Gradient Boosting Machine**: A gradient-boosting architecture based on decision trees that improve model efficiency while reducing memory usage (Ke et al. 2017).
(5) **Gradient Boosting Classifier**: Gradient boosting is an ML technique for regression and classification problems that generate a prediction model in the form of an ensemble of weak prediction models, often decision trees.
(6) **AdaBoost Classifier**: It is a meta-learner that starts by fitting a regressor on the original dataset and then includes new copies of the regressor on the same dataset with the weights of instances changed based on the current prediction error (Kégl 2013).
(7) **Ridge Classifier**: Ridge Classifier is a method that solves a high covariance problem using regularization L2-norm, even if the errors come from an irregular distribution.
(8) **Linear Discriminant Analysis (LDA)**: Fisher's linear discriminant, a method used in statistics and other domains to determine a linear combination of features that characterizes or separates two or more classes of objects or events, is generalized by LDA. The resulting combination can be used as a linear classifier or, more typically, to reduce dimensionality before further classification.
(9) **Logistic Regression Classifier**: The logistic classifier model is a classification model in which the conditional probability of one of the two possible realizations of the output variable is assumed to be equal to a linear combination of the input variables, transformed by the logistic function.
(10) **Naive Bayes**: Naive Bayes methods are a set of supervised learning algorithms based on applying Bayes' theorem with the "naive" assumption of conditional independence between every pair of features given the value of the class variable (Hastie 2001).
(11) **Support Vector Machines (SVMs)**: Each data item in the SVM method represents a point in n-dimensional space, with the value of each feature being the value of a specific coordinate. The classification is accomplished by locating the hyperplane that best distinguishes the two classes (Cortes et al. 1995).
(12) **Quadratic Discriminant Analysis (QDA)**: QDA is a generative model based on the assumption that each class has a Gaussian distribution. The proportion of data points that belong to the class is the class-specific prior. The class-specific mean vector is the average of the class's input variables.

It must be noted that ML can analyze enormous amounts of data to reveal specific trends, patterns, and correlations in data that people would not be able to detect otherwise. For example, understanding the mechanisms of massive windthrows is a helpful tool for predicting disturbance events like the one under consideration. An ML model's fundamental goal is generalization. The capacity of a given model to adapt effectively to additional, previously unseen data collected from the same distribution as the one used to generate the model is referred to as generalization. It is a term that shows how well a trained model classifies or anticipates unobservable data. As ML algorithms gain experience, their accuracy, and efficiency improve. This enables people to make more informed selections. As the amount of data increases, ML algorithms learn to make more accurate predictions faster. It should be taken into account that a plethora of data and data diversity are not the only considerations to be addressed in order to have a generalized model.

An ML model's generalization ability can be measured using inference accuracy, precision, recall, and F1-score. These are conventional metrics of inference accuracy or error for the trained ML model's unknown input data (test data) rather than performance measures for the training data. To evaluate the generalization performance after the verification and verify the hyperparameters of the constructed model, we employed an unknown test set that did not include the training data. This validation method, known as cross-validation, is the most accurate in the literature.

The created ML model is tailored to the training data. If the training does not produce enough essential features, test set performance will be characterized by poor generalization due to overfitting or underfitting. In this instance, a method for efficiently estimating the learning progress should be considered in terms of learning measures. The suggested methodology considers the learning curves in the inference error rate for overfitting and underfitting. If the generalization performance is poor, there is a significant gap between the test and validation. Overfitting frequently raises the error rate as training advances.

Furthermore, when the training data is skewed, the inference's accuracy cannot guarantee a likelihood. The Receiver Operating Characteristic (ROC) curve is a graph that compares epochs or data size with inference accuracy, and generalization performance is demonstrated when a particular threshold is reached. When the curve reaches this point, it is said to be saturated. Lowering the categorization threshold causes more items to be classified as positive, which increases both False Positives and True Positives.

As a proof of the supremacy of the algorithm over the other candidates, the following schematic diagrams (Fig. 3–5 and Fig. 1A-8A, see Appendix) are presented confirming the efficiency of the said algorithm. In general, evaluation metrics are used to measure the performance of an ML method. Without these evaluation metrics, there can be no comparison between algorithms, nor is there the potential to select the appropriate tune hyperparameters that allow the model to maximize model performance. Evaluation is carried out only in the unknown data (test set) as an algorithm may be consistent with the training set but fail to perform well in the test set (Raschka 2014).

The most popular performance metrics that are capable of evaluating and comparing with clarity, thoroughness, and objectivity, the classification algorithms used in this paper are presented below (Talingdan 2019):

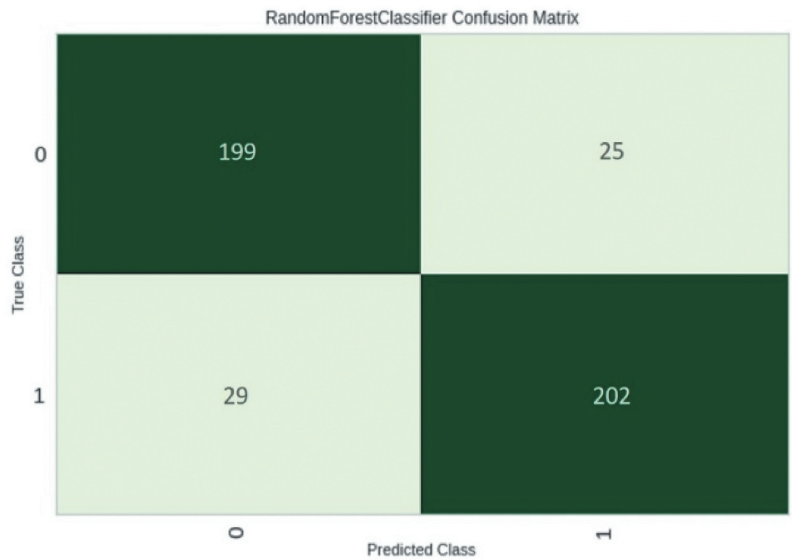

Figure 3. Random Forest Classifier confusion matrix.

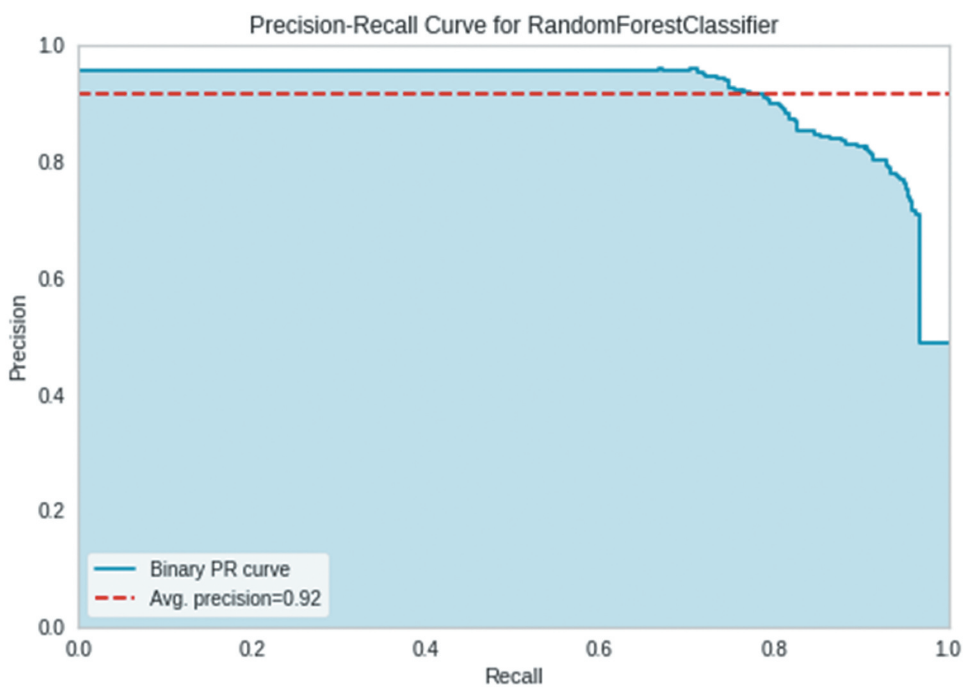

Figure 4. Precision vs recall curve for the Random Forest Classifier.

Confusion matrix

The evaluation of a classification model is based on the number of records in a test set that are predicted correctly or incorrectly by the model. This number is placed in a confusion matrix, a two-dimensional table, in which columns correspond to the predicted and rows to the actual values of each class.

The confusion matrix gives the precise information required to evaluate the damage prediction model. This information is used to compare the effectiveness of the compared models. The number of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) classifications for each class was used to calculate the performance metrics of the trees uprooted. Also, it depicts each combination of true and anticipated classes for the dataset used. The true model forecasts that are 100% accurate are highlighted in green. The line from the TP in the top-left corner to the TN in the bottom-right corner includes the majority of the correct predictions of the trees uprooted in the confusion matrix compared to the class's actual values (Figure 3).

Accuracy

Accuracy is calculated via the following equation (Equation 1):

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

and expresses the percentage of correct predictions.

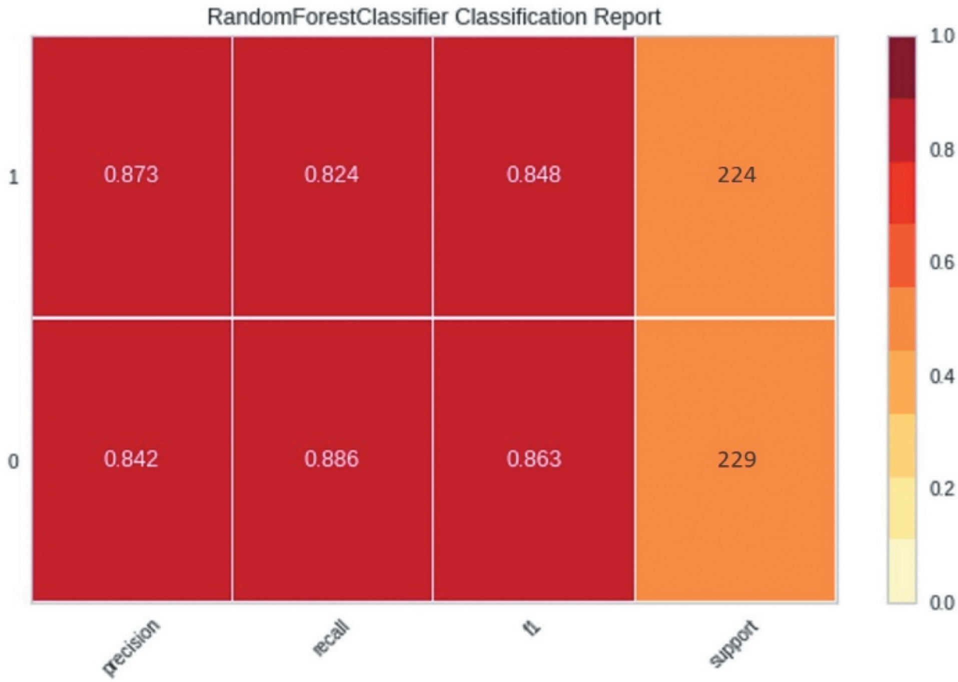

Figure 5. Classification performance report for the Random Forest Classifier.

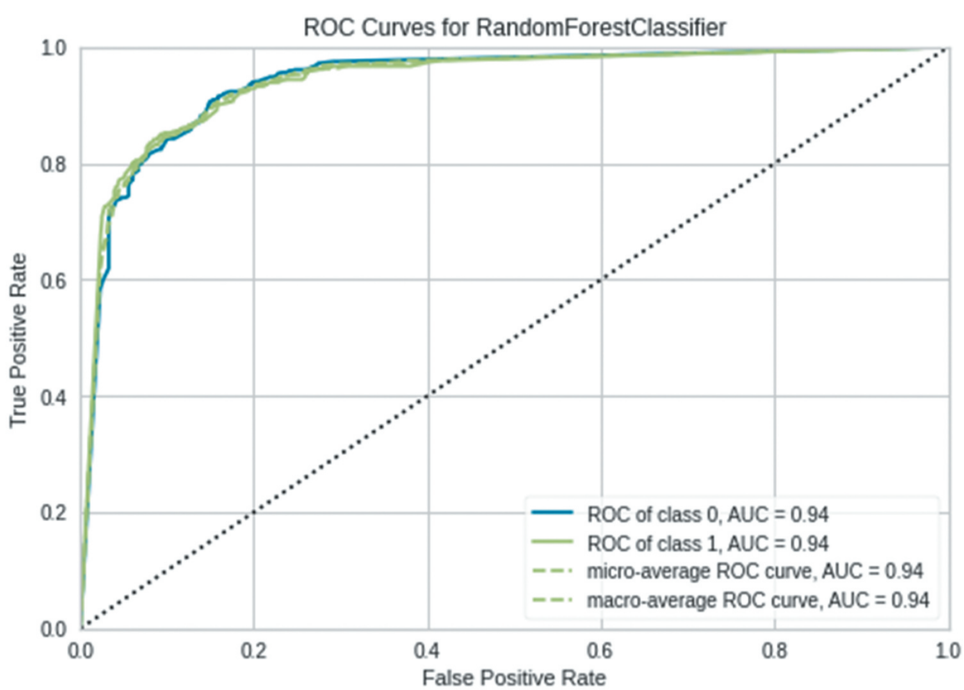

Figure 6. ROC plots for the Random Forest Classifier.

Using accuracy as a defining metric for our model makes sense intuitively. Ideally, we would like to avoid potential problems that could be caused if we predicted that a tree was uprooted, but our model classified it as not uprooted (aim for high recall). Although we do aim for high precision and high recall values, achieving both at the same time is not possible. For example, if we change the model to one giving us high recall, we might detect all the trees that have actually been uprooted, but we might end up protecting areas that have not suffered windthrow damage. Similarly, if we aim for high precision to avoid taking any wrong and unrequired decisions, we might end up identifying a great number of windthrown areas that are actually in need of protection as requiring no protection at all.

Precision

Precision is calculated as follows (Equation 2):

$$precision = \frac{TP}{TP + FP} \quad (2)$$

and expresses the percentage of the correct positive results predicted by the classifier.

Recall

Recall is calculated by means of the following (Equation 3):

$$recall = \frac{TP}{TP + FN} \quad (3)$$

and expresses the classification percentage of all positive results classified by the classifier.

F-score

In order to effectively deal with instances in which a classifier has high recall but low precision, the F-Score metric has been introduced, which is the harmonic mean between precision and recall and is calculated through the following (Equation 4):

$$F_{Score} = \frac{2 \times recall \times precision}{recall + precision} = \frac{2TP}{2TP + FP + FN} \quad (4)$$

The greater the F-Score, the higher are recall and precision and the better is the performance of a given model.

Instead of balancing precision and recall, we can just aim for a good F1-score and that would be indicative of good Precision and a good Recall value as well.

Receiver Operating Characteristic (ROC)

This metric can be applied to classifiers that have confidence as output. In this case, the classifier predicts a class if confidence in this class exceeds a given threshold. For the formation of the ROC curve, various threshold values are used, and each time, the rates [True Positive Rate (TPR) and False Positive Rate (FPR)] are recorded. These pairs of values are plotted in a graph, in which the y axis corresponds to TPR and the x axis corresponds to FPR. The performance of each classifier is represented as a point in the ROC curve as depicted in Figure 6 (Alam et al. 2011).

In order to have an objective evaluation process of ML models, both as a self-evaluation and for comparison with alternative models, numerous statistical techniques for the distribution and processing of datasets, also known as validation techniques, can be used. The most frequent cross-validation approach is k-Fold, which divides the dataset into k subsets, each with an approximately equal population. The all-theoretic compound of the remaining k-1 subgroups is utilized as a training subset, while one of the k-above subsets is employed as a test subset. A total of k computation cycles are conducted, each k subset serving as a test subset. The benefit of this evaluation method is that each data set is used once for training and once for testing. The parameter k can have any positive integer value. However, the most common choice in practical applications used in this paper is $k = 10$, known as 10-Fold Cross Validation (Talingdan 2019).

The pre-processing of data aims to phase out problems that emerge during the selection of data, e.g., extreme values, outliers, missing data, etc. To handle the missing data problem, six records were removed. These records had gaps in some parameters. So, the final data set comprised 455 cases. Also, in order to determine if the dataset included extreme values and outliers, the Interquartile Range method was applied. Extreme values or outliers are points that are far away from the average value of a parameter. The distance is measured based on a threshold which is a multiplicand of the standard deviation. The above analysis was performed without raising extreme values or outliers. Finally, in order to eliminate the likelihood of high values prevailing by influencing the cost function, without nevertheless being more critical, the data were normalized so as to be in the same range using the min-max method in the interval [−1, +1].

Results

After scanning with the help of a UAS an area of approximately 159 ha (Table 1), four damaged plots were identified (aPISY, bPISY, aPIAB, and bPIAB), each of which was located in a different stand. In the first two plots (aPISY and bPISY), belonging to two mixed stands of conifers and broadleaves, namely *Pinus sylvestris* and *Quercus sp*., damage had only occurred in *Pinus sylvestris*. In the other two plots (aPIAB and bPIAB), also belonging to another two mixed stands of *Fagus sylvatica* and *Pinus sylvestris*, damage had only occurred in the secondary species, i.e., *Picea abies*.

Table 3 illustrates the topographic features as well as the size of each plot, the largest of them being aPIAB with 5.75 ha. These plots are located at altitudes ranging from 1000 to 1300 m. Table 4 shows the ranking of the severity of damage in these plots following the Bradford/Unwin damage scale (Unwin et al. 1988). According to this scale, damage equal to 1.5 is considered as a serious disturbance. Plot aPISY, with a large number of trees being snapped or uprooted and the rest having undergone moderate disturbance, belongs to this class

Table 3. Topographic features and size of plots.

Plots	Latitude	Longitude	Geology	Aspect	Altitude	Slope (%)	Area (Ha)
aPISY*	41° 15′ 46′′ N	024° 45′ 48′′ E	granite	SW	1000	10	1.20
bPISY	41° 15′ 32′′ N	024° 46′ 06′′ E	granite	S	1000	40	4.10
aPIAB**	41° 20′ 37′′ N	024° 42′ 21′′ E	rhyolite	NW	1300	20	5.75
bPIAB	41° 20′ 40′′ N	024° 42′ 22′′ E	rhyolite	NW	1300	20	0.26
Sum							11.31

* *Pinus sylvestris*, ** *Picea abies*

Table 4. Damage severity according to Bradford/Unwin damage scale, number of damaged trees per plot, type of damage, and damage in $m^{3.}$

Plot	Bradford/unwin damage scale	Level of damage	Number of stems assessed	% uprooting	DBH (SD)	Damage m^3/species **
aPISY(27a)	1.5 (95%)*	Severe	26	65.38	23.33 (4.43)	4.69
bPISY(26c)	1 (100%)	Severe	237	39.66	21.46 (2.28)	33.08
aPIAB(7a)	3 (9%)	Moderate	160	88.75	26.07 (8.00)	77.88
bPIAB(7b)	2.5 (20%)	Moderate	34	52.94	25.27 (8.28)	9.19
sum			457			124.84

(%)*percentage of damaged trees.
**uprooted trees (m^3).

Table 5. Uprooting percentage in relation to total damage for both species and per species.

	Uprooted	
PISY	111/457* (24.29%)	111/263** (42.20%)
PIAB	160/457 (35.01%)	160/194** (82.47%)

* Total damaged trees (uprooted and snapped) for both species (PISY: *Pinus sylvestris* and PIAB: *Picea* abies).
** Total damaged trees (uprooted and snapped) per species.

(Table 4). Damage equal to 1.0 corresponds to severe and extensive disturbance; plot bPISY falls into this class as all the trees exhibited extensive disturbance.

Damage equal to 3 corresponds to moderate or minor disturbances; plot aPIAB belongs here, as fewer than 10% of the trees were damaged (Unwin et al. 1988; Metcalfe 2008). In this plot, 160 *Picea abies* trees were affected, 88.75% of which were uprooted and the remaining snapped. Last, plot bPIAB belongs to scale 2.5, which is considered to represent instances of moderate disturbance, where fewer than 33% of the trees were found to be broken or uprooted. Table 4 also shows the diameters at breast height of the uprooted trees as well as the wood volumes of the uprooted trees per plot.

Table 5 depicts the total number as well as the percentage of the uprooted trees per species (111 *Pinus sylvestris*, 160 *Picea abies*) compared to the total number of damaged trees (457), which includes both the uprooted and snapped trees; the latter, however, were not taken into consideration in the present study. The table also shows (3rd column) the number and percentage of the uprooted trees per species (263 *Pinus sylvestris*, 194 *Picea abies*) compared to the total number of uprooted trees.

In the present study, the following ML methods were evaluated and compared to identify a predictive model for forecasting disasters at tree-level data: Random Forest Classifier (Breiman 2001), *k*-Neighbors Classifier (Bremner et al. 2005), Decision Tree Classifier (Kamiński et al. 2017), Light Gradient Boosting Machine, Gradient Boosting Classifier (Elith et al. 2008), Ada Boost Classifier, Ridge Classifier, Linear Discriminant Analysis, Logistic Regression (Bishop 2006) Naive Bayes, SVM – Linear Kernel and Quadratic Discriminant Analysis (Cortes and Vapnik 1995). In order to get the best predictive model, the different ML algorithms were evaluated based on six performance metrics (confusion matrix, accuracy, precision, recall, F1-score, and ROC).

It must be noted that the proposed binary classification method has some substantial advantages. Specifically, it is very fast compared to the other multi-classification methods, performs well in large and small datasets, can easily handle irrelevant features, is free of complexity and can be easily handled by non-expert users.

Table 6 illustrates the results of the comparative study.

Winner algorithm

The algorithm with the best predictive performance as reflected in Table 6 was found to be Random Forest (RF) (Prinzie and Poel 2007). RF uses decision trees as predictive models, to which it assigns comments and conclusions regarding the target value of the dependent variable. Each decision tree is calculated by induction, based on the recorded data, using the divide-and-conquer technique. More specifically, for the data set considered in the present paper, each datum includes seven independent variables and there are a total of two classes (C_1,C_2) as independent variables (uprooted vs. not uprooted).

The objective is the partition of the set into subsets, each of which comprises data belonging to a single class. In particular, a suitable test is selected, which typically uses a single feature, with only one output in the set $\{O_1,O_2,\ldots,O_n\}$. In this way, the set is partitioned in subsets $T_1,T_2,\ldots,T_n$, where subset T_i includes all the data of the initial set for which the O_i output

Table 6. Machine learning performance comparison results.

ID	Algorithm	Accuracy	ROC	Recall	Precision	F-Score	TT (Sec)
1.	Random Forest Classifier	0.8851	0.9476	0.8677	0.8975	0.8820	0.610
2.	k-Neighbors Classifier	0.8838	0.9433	0.8719	0.8917	0.8811	0.126
3.	Decision Tree Classifier	0.8827	0.9030	0.8573	0.9019	0.8785	0.020
4.	Light Gradient Boosting Machine	0.8745	0.9450	0.8407	0.8997	0.8689	0.121
5.	Gradient Boosting Classifier	0.8468	0.9221	0.7874	0.8909	0.8356	0.192
6.	Ada Boost Classifier	0.7662	0.8480	0.6655	0.8288	0.7376	0.160
7.	Ridge Classifier	0.7559	0.0000	0.6634	0.8091	0.7286	0.016
8.	Linear Discriminant Analysis	0.7559	0.7625	0.6634	0.8091	0.7286	0.020
9.	Logistic Regression	0.7542	0.7687	0.6565	0.8110	0.7253	0.359
10.	Naive Bayes	0.7391	0.7773	0.6856	0.7635	0.7220	0.018
11.	SVM – Linear Kernel	0.6370	0.0000	0.7686	0.6947	0.6735	0.030
12.	Quadratic Discriminant Analysis	0.5146	0.4607	0.1215	0.8495	0.1078	0.018

has been derived. So, the decision tree includes a decision node where the test selected is performed and a branch for each $O_1, O_2, \ldots, O_n$ output. It should be stressed that the RF algorithm uses a large number of decision trees in order to correctly achieve the final categorization of the problem at hand.

Discussion

The Fujita (F) Scale is used to estimate tornado wind speeds based on the level of damage left behind by a tornado. The scale ranges from F0, assigned to tornadoes that generate "light damage," to F5, which is assigned to tornadoes causing "incredible damage." According to Canham et al. (2001), severe tornadoes rated F3-F5 on the Fujita scale with winds blowing at >70 m/s (Godfrey et al. 2017) may cause uniform and complete windthrow in a location with relatively distinct boundaries between the damaged area and an adjacent minimally disturbed site. The majority of tornadoes (almost 75%) correspond to an F-scale rating of F0-F1 and are characterized by moderate winds (<50 m/s); however, they are likely to bring about a wide range of catastrophic impacts on the affected trees. In the current research, carried out in an area NE of the City of Xanthi, on April 5, wind speeds were well below 50 m/s (9.4 m/s) and blew constantly without pause for the next 2 days (6 and 7 April), on which speeds amounted to 11.8 m/s and 10.7 m/s, respectively. These winds produced damage rated between F0-F1 on the Fujita scale (Godfrey and Peterson 2017).

As also mentioned in the Materials and Methods section, in the present study, we used data from an airborne unmanned aircraft system (UAS). The detection of windthrow is commonly carried out with the use of imagery from both airborne (airborne optical sensors, airborne laser scanning [ALS], synthetic aperture radar [SAR]) and spaceborne (spaceborne optical system, spaceborne exact repeat track SAR, spaceborne LRW SAR [multi-track]) sources (Rüetschi 2019).

Field surveys of windthrown areas either stand-alone or in combination with the interpretation of aerial imagery (the method followed in the present study) are considered time-consuming and expensive (Rüetschi et al. 2019). Besides that, the areas that can be covered by all the airborne sensing systems tend to be smaller sized in comparison with those covered by spaceborne means, and the optical data of their imagery are dependent on the prevailing weather conditions (Rüetschi et al. 2019; Honkavaara et al. 2013; Mokroš et al. 2017; Duan et al. 2017; Nyström et al. 2014; Polewski et al. 2018), a fact that is not the case with spaceborne systems (Dyukarev et al. 2011; Eriksson et al. 2012; Jonikaviˇcius et al. 2013; Baumann et al. 2014; Elatawneh et al. 2014; Einzmann et al. 2017; Tanase 2018).

However, UASs have a certain number of advantages over the other airborne systems (ALS, SAR); firstly, they are capable of detecting windthrown areas smaller than 0.5 ha (Rüetschi et al. 2019), as is the case with plot bPIAB in the current study whose area is 0.26 ha (Table 3). In addition, unlike ALS or SAR (Rüetschi et al. 2019), they allow the detection of individual windthrown trees (Honkavaara et al. 2013; Mokroš et al. 2017; Duan et al. 2017) (in the present research, individual windthrow was detected in aPIAB and bPIAB plots).

Moreover, UASs are not dependent on low temperatures (Way et al. 1990), unlike SARs, whose backscatter in low temperatures is negatively affected by object properties. More specifically, low temperatures in wood (Way et al. 1990), especially below the freezing point (Wegmüller et al. 1994), wet snow (Koskinen et al. 1997), as well as the internal and external moisture conditions (Proisy et al. 2000; Sharma et al. 2005) are likely to affect backscatter from forested areas. Finally, UASs are not dependent on the structural properties of a forest, such as size, aspect, and the spatial pattern of the trees as a whole, as well as their branches and leaves (Westman et al. 1987; Dobson et al. 1992; Imhoff et al. 1995).

Future environmental conditions are expected to be particularly unstable due to climate change. In this context, fostering species diversity is a particularly suitable management approach acknowledged by a growing body of research (Knoke et al. 2008; Griess et al. 2012; Neuner et al. 2015). Tree species diversity significantly contributes to the resilience of forest ecosystems and their resistance to the impacts of natural disturbances (Silva Pedro et al. 2015).

Diversity ensures that even if the performance of a given tree species declines or fails under certain conditions, other species with different characteristics become better adapted to or resist the same extreme environmental drivers and maintain ecosystem functionality. Diverse characteristics increase the likelihood of the ecosystem's positive response to disturbance impacts, thus increasing ecosystem resilience, resistance, and, hence, rejuvenation (Mori et al. 2013).

All the windthrown plots of the present study (plots aPISY, bPISY, aPIAB, and bPIAB) were located in mixed stands of different spatial grain of mixing tree species. Despite the consensus in the relevant literature on the benefits of species diversity, the effects of the spatial grain of mixing three species have not yet been systematically investigated (Sebald et al. 2021).

Sebald et al. (2021) studied diversity effects between stands, which they termed *beta diversity*, and compared them with the effects of within-stand diversity (*alpha diversity*). While the effects of the latter have already been explored extensively (Del Río et al. 2017; Guyot et al. 2016; Huang et al. 2018), beta diversity has received relatively little attention.

In plots aPISY and bPISY, consisting solely of *Pinus sylvestris*, 95–100% of the trees were blown down. However, the greatest extent of uprooting measured in m^3 of damaged wood (77.88 m^3, Table 4) occurred in plot aPIAB, as it was the largest disturbed plot in size (5.75 ha, Table 3). As a rule, it was observed that in all four mixed stands of conifers and broadleaves (Table 1), only the conifers, i.e., *Pinus sylvestris* and *Picea abies* were affected, while the broadleaves (*Fagus sylvatica* and *Quercus sp.*) showed no signs of damage.

In the first two mixed stands (PsMxQu and PsDomxQu), both of which were made up of conifers and broadleaves (*Pinus sylvestris* and *Quercus sp.*), and more specifically, in plots aPISY and bPISY (corresponding to PsMxQu and PsDomxQu stands, respectively, Table 1), disturbance occurred only in *Pinus sylvestris* trees, as these plots were composed solely of *Pinus sylvestris*. In these plots, tree species mixing was between stands (beta diversity) (Sebald et al. 2021). In the other two mixed *Pinus sylvestris* and *Fagus sylvatica* plots, i.e., aPIAB and bPIAB (belonging to stands FsDomxPs and PsDomxFs, respectively), disturbance occurred only in a secondary species, namely *Picea abies*, a fact that can serve as proof that *Fagus sylvatica* is exceptionally resistant to overturning or breaking in the given weather conditions, a fact that is also corroborated by Schmidt et al. (2010). This is true only if *Fagus sylvatica* is not affected by beech bark disease, as in the present case. In these plots, tree species mixing was within stands (alpha diversity) (Sebald et al. 2021).

By comparing the four plots, it can be seen that mixing tree species within a stand, such as in aPIAB and bPIAB plots (alpha diversity), is more effective in buffering disturbance impacts than mixing tree species between stands (beta diversity, aPISY and bPISY plots), a result that is not consistent with the study by Sebald et al. (2021), who argue that fostering beta diversity can be as effective or even more effective than alpha diversity.

In the same study (Sebald et al. 2021), it is also claimed that in high elevation conditions (e.g., Dischma landscape) mixing tree species within a stand has stronger positive effects on biomass stocks (alpha diversity) (Larocque et al. 2013; Morin et al. 2018), a fact that is consistent with the results of the present research in which all windthrown plots are located at a considerably high altitude (1000–1300 m, Table 3).

Increasing tree species diversity, however, may not be enough to deter the multiple impacts of global change (Sebald et al. 2021) and may need to be accompanied by additional measures such as increasing resistance through thinning and reduced rotation periods (Zimová et al. 2020) or increasing resilience through advance regeneration (Johnstone et al. 2016) and enhanced structural diversity (Millar et al. 2007).

In the present paper, where *Pinus sylvestris* was mixed either with *Quercus sp*. or with *Fagus sylvatica* (aPIAB, bPIAB), it had been substantially protected, while in those plots where it stood on its own (aPISY, bPISY), it was extensively uprooted. On the other hand, *Picea abies*, even if it was mixed with *Fagus sylvatica* and *Pinus sylvestris*, had been blown down to a large extent.

The ability of a tree to withstand trunk breakage is determined by the applied load (wind speed), tree geometry (crown sail-area and stem taper), as well as the mechanical properties of green wood, i.e., compression strength and modulus of elasticity (Horáček 2003). Taking into consideration the fact that the mechanical properties of green (moist) wood differ from those of industrial wood (Brudi et al. 2002), we used the corresponding green wood values in accordance with the Stuttgart table of wood strength (Wessolly and Erb 1998) and, in particular, those for *Pinus sylvestris, Picea abies, Fagus sylvatica* and *Quercus sp*. (Table 2). Wessolly and Erb (1998) studied the behavior of standing trees by means of an elastometer and derived the values of the mechanical properties of green (moist) wood (Horáček 2003).

Stiffness, measured by the modulus of elasticity (N/mm^2), is the only constant of materials that is responsible for the behavior of the trunk under load stress such as the power of the wind. The destruction of a trunk takes place when the wind-induced stress on the marginal fibers of the trunk exceeds the tree's resistance to compression and this capacity to withstand loads is referred to as *compression strength*.

The resistance of a tree's crown to the wind is also expressed by means of the aerodynamic drag factor (c_w). The drag factor shows that during a storm, the leaves, branches, and smaller twigs are bent by powerful air gusts (Mayhead 1973). *Fagus sylvatica's* green wood is significantly more rigid (E_{mod} = 8500 N/mm^2) and has stronger compressive properties (22.5 N/mm^2) than *Pinus sylvestris* and *Picea abies*; also, the green wood of *Quercus sp*. has the highest compression strength (28 n/mm^2) compared to the other three species.

In addition, both broadleaved species have very high aerodynamic drag factor values (c_w = 0.25–0.30 and c_w = 0.25 for *Fagus sylvatica* and *Quercus sp*., respectively), with c_w = 0.30 being the maximum limit. *Pinus sylvestris* does not have very high stiffness values (E_{mod} = 5800 N/mm^2) or particularly strong compressive properties (17 N/mm^2) and at the same time exhibits a relatively low aerodynamic drag factor (c_w = 0.15), a fact that justifies the high rates of *Pinus sylvestris* uprooting (42.20%).

Picea abies, on the other hand, is more resistant to external loads (E_{mod} = 9000 N/mm^2) compared to *Pinus sylvestris*, so it can be considered that its green wood is more rigid and has stronger compressive properties (21 N/mm^2); its aerodynamic drag factor has a moderate value (c_w = 0.20), which is by all means higher than that of *Pinus sylvestris* (c_w = 0.15). The high rates of uprooting in this species (82.47%) are probably due to the fact that *Picea abies* is shallow rooted.

Conclusions

In the disturbed area, located NE of the City of Xanthi, *Pinus sylvestris* and *Picea abies* individuals suffered damage from stormy winds blowing for three consecutive days in 2020 with maximum gusts reaching 187.5 km/h (on April 5th) and maximum wind speeds equal to 11.8 m/s. According to the Fujita scale, the above wind speeds are ranked F0-F1, a category comprising almost 75% of tornadoes (Godfrey 2017). As the winds were not considered to be particularly strong, the disturbance caused was not significantly extensive. Four plots in the study area were affected with a total area equal to 11.31 ha (Table 3). The damage due to uprooting amounted to 124.84 m^3 of wood (Table 4), while the overall damage including windsnap was 187.77 m^3.

Mechanized harvesting constitutes an economical method of salvage logging as it secures high productivity (Magagnotti, 2013) and offers improved occupational safety especially in harsh harvesting conditions due to windthrows. Fully mechanized harvesting systems are not in use in Greece. In the current study, salvage logging was based on a highly mechanized system (with chainsaws and cable yarder and tractor). According to Oprea (2008), the use of highly mechanized harvesting systems is not recommended when timber is scattered in large areas

Identifying the plots where the damage occurred was a problematic task as these areas were small-sized and scattered, and consequently it was highly unlikely that they could be identified through satellite. In order to identify the disturbed plots, an unmanned aircraft system (UAS) was used in the present study, as these systems are, as a rule, flexible and easy to use. It is beyond doubt that it is of crucial importance to quickly detect all damaged trees from abiotic causes such as wind disturbance even if they are scattered and in small areas as they constitute habitats to bark beetles (Seidl et al. 2014).

While recording and analyzing the information we collected about the damaged trees, it became easily evident that *Picea abies* is highly unstable and therefore easily uprooted even in low wind speeds, and its individuals are unable to be protected even if it is a secondary species within mixed conifer-broadleaf clusters. Schmidt et al. (2010) also agree that *Picea abies* is more susceptible to disturbance and argue that enhancing tree species diversity with *Pinus sylvestris* mitigates disturbance impacts to a great extent. According to the Stuttgart table of wood strength (Wessolly and Erb 1998), the green wood of *Picea abies* has relatively good mechanical resistance and presents sufficient stiffness (E_{mod} = 9000 N/mm^2), but its easy uprooting is due to its shallow root system that provides rather poor anchorage (Puhe 2003).

It was also found that, unlike *Picea abies*, under the same wind conditions, *Pinus sylvestris* experienced disturbance not individually but only in relatively small plots (1.20 ha and 4.10 ha, respectively, was the total area of plots aPISY and bPISY, where almost all *Pinus sylvestris* trees [95% and 100%, respectively] had been damaged). From on-site research, the authors assumed that a large proportion of damage within the respective plots can be attributed to trees falling on their neighbors (Metcalfe et al. 2008). It was also found that in those cases where *Pinus sylvestris* was mixed with *Fagus sylvatica* in a cluster, it had been protected, whereas if it stood alone, it was damaged. Taking into account the fact that wind speeds were not exceptionally high as compared to those in other disturbed areas, it can also be assumed that the topographic conditions of the plots (slope, aspect, etc.) played a role in affecting local wind conditions, such as speed and pressure (Brudi and Wassenaer 2002; Metcalfe et al. 2008; Einzmann 2017).

Given the global climate change situation, the approaches to be adopted for the optimal management of forests should revolve around goals of forest resilience and effective adaptation to future demanding environmental conditions. The authors of the current study believe that the windthrow data provided herein will benefit policy decision makers regarding risk management and forest planning. To this end, the following recommendations might prove useful.

It is deemed necessary to opt for mixed forests and avoid large monoculture patches where a certain species develops on its own, as in the case of *Pinus sylvestris*, since it has been shown that even in relatively low wind intensities there may be serious tree damage; it is also recommended that *Picea abies* be avoided as it is particularly susceptible to windthrow even in relatively low wind intensities, and it is hardly protected even in a mixed conifer-broadleaf community.

The data collected was used to develop a realistic machine learning model (Demertzis et al. 2017) which adopts an RF algorithm in order to predict windthrow in similar conditions. The methodology of the proposed information system utilizes and expands the most technologically advanced forestry methods, as it takes advantage of the hidden knowledge lying in environmental data in order to add to climate change analysis methods and optimal decision-making mechanisms associated with it. The key to the success of the proposed method is how well the proposed ML model can be generalized. The term "generalization" refers to the model's capability to adapt and react appropriately to previously unseen new data, which has been drawn from the same distribution as the one used to build the model. In other words, generalization examines how well a model can digest new data and make correct predictions after being trained on a training dataset. With a robust ML model like the proposed one, small-scale or no upgrades are needed because the prediction model readjusts itself to fit with the trend at hand at each particular time. This can be used to carry out any function possibly relevant to damage or the prediction of other environmental problems. These intelligent operations can help collate relevant or hidden information and can predict the occurrence of numerous disturbance events before they occur.

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