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► **To cite this version:**

Emma Hart, Kevin Sim, Kana Kamimura, Céline Meredieu, Dominique Guyon, et al.. Use of machine learning techniques to model wind damage to forests. *Agricultural and Forest Meteorology*, 2019, 265, pp.16-29. 10.1016/j.agrformet.2018.10.022 . hal-02624477

HAL Id: hal-02624477

<https://hal.inrae.fr/hal-02624477v1>

Submitted on 26 Sep 2024

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Use of Machine Learning Techniques to Model Wind Damage to Forests

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Highlights

Use of Machine Learning Techniques to Model Wind Damage to Forests

1. Machine learning techniques were accurate in predicting wind damage to trees.
2. Random forests proved the most accurate and discriminating methodology.
3. Models were sensitive to removal of site and stand but not tree characteristics.
4. All models were able to accurately replicate a mechanistic wind risk model.
5. Machine learning techniques could help the management of wind damage to forests.

1 **Abstract**

2 This paper tested the ability of machine learning techniques, namely artificial neural networks and random forests, to
3 predict the individual trees within a forest most at risk of damage in storms. Models based on these techniques were
4 developed individually for both a small forest area containing a set of 29 permanent sample plots that were damaged in
5 Storm Martin in December 1999, and from a much larger set of 235 forest inventory data damaged in Storm Klaus in
6 January 2009. Both data sets are within the Landes de Gascogne Forest in Nouvelle Aquitaine, France. The models were
7 tested both against the data from which they were developed, and against the data set from the other storm. For
8 comparison with an earlier study using the same data, logistic regression models were also developed. In addition, the
9 ability of machine learning techniques to substitute for a mechanistic wind damage risk model by training them with
10 previous mechanistic model predictions was tested.

11
12 All models were accurate at identifying whether trees would be damaged or not damaged but the random forests models
13 were more accurate, had higher discriminatory power, and were almost totally unaffected by the removal of any
14 individual input variable. However, if all information relating to a stand was removed the random forests model lost
15 accuracy and discriminatory power. The other models were similarly affected by the removal of all site information but
16 none of the models were affected by removal of all tree information, suggesting that damage in the Landes de Gascogne
17 Forest occurs at stand scale and is not controlled by individual tree characteristics. The models developed with the large
18 comprehensive database were also accurate in identifying damaged trees when applied to the small forest data damaged
19 in the earlier storm. However, none of the models developed with the smaller forest data set could successfully
20 discriminate between damaged and undamaged trees when applied across the whole landscape. All models were very
21 successful in replicating the predictions of the mechanistic wind risk model and using them as a substitute for the
22 mechanistic model predictions of critical wind speed did not affect the damage model results.

23
24 Overall the results suggest that random forests provide a significant advantage over other statistical modelling techniques
25 and the random forest models were found to be more robust in their predictions if all input variables were not available.
26 In addition, the ability to replace the mechanistic wind damage model suggests that random forests could provide a
27 powerful tool for damage risk assessment at the stand or single tree level over large regions and provide rapid assessment
28 of the impact of different management strategies or be used in the development of optimised forest management with
29 multiple objectives and constraints including the risk of wind damage.

30
31 Machine learning; forest damage; wind risk, risk models, GALES, forest planning

32 **1. Introduction**

33 Wind causes more than 50% by volume of all damage to European forests and is the major damage agent on the
34 continent (Schelhaas et al., 2003). On average 2 storms each year cause major damage in some part of Europe, where
35 major damage is defined as disrupting the normal harvesting and supply of timber in a region. In south-west France there
36 have been two major storms in the recent past that have threatened the viability of the forest industry in the Nouvelle
37 Aquitaine region. On 27 December 1999 Storm Martin caused a loss of 26 million m³ of timber (equivalent to 3.5 years
38 of normal harvest) in the north of the region and on 24 January 2009 Storm Klaus caused 41 million m³ of timber loss
39 further south. The damage was predominately (37 million m³) to maritime pine (*Pinus pinaster*Ait.) and the damage from
40 the two storms represented 15% and 32% of the maritime pine standing volume in the region respectively.

41

42 There are also now increasing concerns that wind damage in Europe and many other parts of the world may increase with
43 the changing climate (Csilléry et al., 2017; Haarsma et al., 2013; Kunkel et al., 2013; Lindner et al., 2010) due to the
44 increasing intensity of low pressure systems whether extra tropical or tropical (hurricanes and typhoons). Therefore, in
45 order to plan for the future there is a need for accurate models predicting tree vulnerability to wind damage and the level
46 of risk. Such wind risk models form part of the risk assessment process that is an integral part of forest management
47 (Cucchi et al., 2005; Gardiner and Welten, 2013; Hanewinkel et al., 2010) and allow managers and planners to decide on
48 choice of species, silvicultural/management approaches, and rotation lengths for forest stands as a function of the site
49 conditions (e.g. soil type, slope, water table depth, wind climate, etc.).

50

51 A number of modelling approaches to wind risk in forests are available. These include mechanistic (Gardiner et al., 2008)
52 and statistical approaches (Albrecht et al., 2010). Previous attempts to model the observed damage patterns in the Landes
53 de Gascogne Forest in Nouvelle Aquitaine, France using these two very different approaches are described in Kamimura
54 et al. (2016). The mechanistic approach used the GALES model (Hale et al., 2015) and the statistical approach was based
55 on logistic regressions (e.g. Valinger and Fridman, 2011). The results showed mixed success. The models were first
56 tested on a small forest area that had a detailed survey of tree characteristics and damage following the Martin storm.
57 Both models made accurate predictions of which individual trees were damaged in the storm. However, when the models
58 were applied across the whole forest at the regional scale the logistic regression model performed poorly and GALES
59 only worked well in areas with similar soil conditions to those from previous tree pulling tests used in the model
60 parameterisation (Cucchi et al., 2004).

61

62 In environmental science there has been an increased use of Artificial Intelligence (AI) techniques in modelling studies

63 (Chen et al., 2008). These techniques have also been increasingly used in forestry (e.g. Lagerquist et al., 2017) although
64 the ideas of using AI in forestry have already been around for a long time (Kourtz, 1990). However, very little attention
65 has been paid to the use of AI in modelling the risk of wind damage with the exception of the work of Hanewinkel (2005)
66 and Hanewinkel et al. (2004) who investigated the use of artificial neural networks. They found that the use of artificial
67 neural networks allowed enhanced identification of damaged trees compared to the more classic approach using a logistic
68 regression model.

69
70 In this paper we present analysis of the data on wind damage at an individual tree level from the Landes de Gascogne
71 Forest using two methods that are based on machine learning (ML) techniques (Alpaydin, 2014). This was to determine
72 if such approaches can provide a better prediction of wind risk than was possible with more conventional approaches as
73 reported by Kamimura et al. (2016). The approach we took were based on artificial neural networks (NN) (Patterson,
74 1996) and random forests (RF) (Breiman, 2001). We also developed logistic regression models (LOG) for comparison
75 with the previous work (designated LR in Kamimura et al. (2016)). We analysed damage from the small Nezer Forest
76 (~80 km²) containing a set of 29 permanent sample plots that were damaged in Storm Martin in December 1999 and from
77 a much larger set of 235 plots from the National Forest Inventory in the Landes de Gascogne Forest (~10,000 km²) that
78 were examined directly after damage from Storm Klaus in January 2009. The purpose was to evaluate the accuracy and
79 discriminatory ability of the models using all available input data and to test the models both on the data set from which
80 they were developed and the other independent data set to see how portable the models were. We wanted to test whether
81 these new approaches provided an improvement in damage prediction and to determine which group of input parameters
82 are most important for model performance. We do not attempt to directly identify the factors controlling the propensity of
83 trees to damage, which has been the subject of numerous previous studies (e.g. Albrecht et al., 2010; Colin et al., 2009;
84 Dobbertin, 2002; Nicoll et al., 2006; Valinger and Fridman, 2011)

85
86 We also tested whether such ML models could replace the mechanistic model GALES by “learning” how to predict the
87 critical wind speed for tree damage from a large number of GALES runs on data representing the range of conditions
88 found in the Landes de Gascogne Forest. The purpose was to determine the potential of providing a faster method of
89 calculating the vulnerability of forests, and one that could be represented in a relatively simple equation. This could allow
90 rapid calculation of risk over large areas and be extremely helpful in testing different management and planning scenarios
91 with the consequences immediately available to the end-users. Such ML models could also be used in optimisation of
92 forest planning when there are multiple objectives and constraints (e.g. risk of wind damage) as previously demonstrated

93 by Zeng et al., (2007).

94

95 **2. Materials and Methods**

96 *2.1. General Approach*

97 The general modelling approach followed was similar to Kamimura et al. (2016) (see their Fig. 2). The main differences
98 are that models were developed separately using the National Forest Inventory data (NFI data), collected after Storm
99 Klaus (Inventaire Forestier National. 2009*), and the Nezer Forest data, collected after Storm Martin (Chehata et al.,
100 2014). The models were developed from each data set using a balanced selection of trees (similar number of undamaged
101 and damaged trees) selected from 90% of the data (see Section 2.3.5 below). The models were then tested against the
102 remaining 10% of the data (Part 2 of Fig. 1). This was repeated 10 times with a different 10% of the data being used for
103 testing each time. Finally, both sets of models were tested with the other independent data by creating 10 versions of each
104 model using a different selection of balanced data and testing against the whole of the other data set. This was to check
105 how transferable the models were and to check their ability to predict the damage from a different storm from the one
106 used in their development. In this paper we did not consider the type of damage (breakage or overturning) but combined
107 all trees known to have been damaged by a storm.

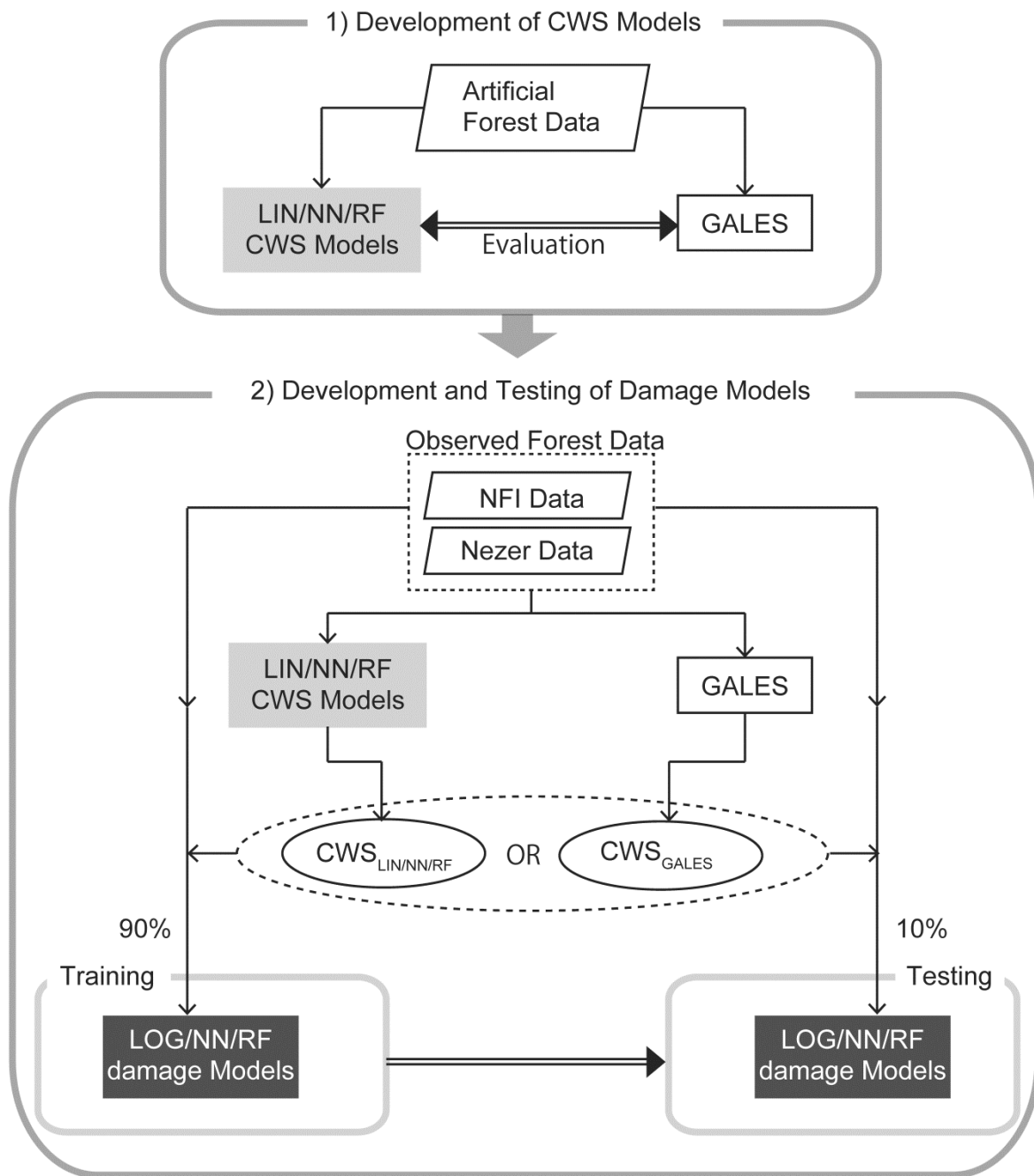
108

109 In addition a set of models was developed to predict critical wind speeds (CWS) using an artificially generated data set to
110 see if it was possible to substitute for GALEs (Part 1 of Fig. 1). CWS calculated both by GALEs and by these GALEs
111 substitute models were subsequently used in the development of the damage models along with characteristics of the
112 individual trees, stand, and site (Part 2 of Fig. 1).

113

114 In the model development and validation we focussed on the CWS and WAsP calculations at 29 m above the ground for
115 the Nezer Forest and at 40 m above the ground for the NFI data. This was to help maintain the focus of the paper and to
116 ensure direct compatibility with Kamimura et al. (2016). Results for other calculation heights are presented in Appendix
117 A and indicated where appropriate.

* <https://inventaire-forestier.ign.fr/spip.php?article610>



118
 119 Fig. 1 Outline of modelling approach (LOG: logistic regression model, LIN: linear regression model, NN: artificial
 120 neural networks, RF: random forests; CWS: critical wind speed). In Part 1 (top) three modelling approaches (LIN, NN,
 121 RF) were trained to predict the CWS for damage based on a very large set (1970 individual trees) of previous simulations
 122 using GALES. In Part 2 (bottom) three modelling approaches (LOG, NN, RF) were trained (left-hand side) to predict
 123 damage using either the NFI or the Nezer Forest data (90% of data from each forest) together with either the GALES
 124 derived CWS, or the CWS values predicted using the models developed in Part 1. This produced a set of damage models
 125 (LOG/NN/RF) based on the Nezer Forest data and a set of damage models based on the NFI data. All damage models
 126 were then tested on the remaining 10% of the appropriate data set (right-hand side). The pattern of training and testing
 127 was repeated 10 times using 90% of the data for the training and a different remaining 10% of the data each time for
 128 validation. Compare with Fig. 2 in Kamimura et al. (2016).

129

130 *2.2. Machine Learning Methods*

131 Loosely inspired by biological neural networks, artificial neural networks (NN) are able to approximate a non-linear
132 function to describe a mapping between a set of inputs and outputs. They are able to learn from incomplete and noisy
133 datasets, making them particularly suitable for applications within forestry where data is hard to collect and likely to
134 contain inaccuracies due to measurement difficulties. Previous applications of NNs in forestry have dealt with mortality
135 estimation (Guan and Gertner, 1995; Hasenauer et al., 2001), and uncertainty assessment of forest growth models (Guan
136 et al., 1997). However, a weakness in the neural network approach is that the learned function describing the non-linear
137 mapping cannot be easily understood in terms of processes controlling behaviour, e.g. wind damage in forests. They are
138 therefore tools that can be of practical use but do not easily provide scientific insight.

139

140 Random forests (RF) are a more recent technique (Breiman, 2001) that have also proved successful in developing models
141 from noisy and unbalanced data. The RF algorithm builds a collection of independent decision trees whose results are
142 combined to make a prediction for a given data record. The technique has the advantage of being very fast to train, and
143 typically overcomes overfitting problems associated with decision tree methods. They are becoming extremely popular in
144 many aspects of forest modelling (e.g. Seidl et al., 2011).

145

146 Logistic regression models (LOG) have been regularly used in assessing the risk of wind damage because their dependent
147 variables are categorical and if the binary dependent variable is binary (0/1) they are ideal for wind damage prediction
148 (damaged/undamaged). In particular, logistic regression models can be used to identify which factors are associated with
149 wind damage. In this paper, a logistic regression model similar to those developed by Albrecht et al. (2012), Valinger and
150 Fridman (2011) and Kamimura et al. (2016) was used.

151

152 *2.3. Software and Methods*

153 The WEKA software "workbench" (Waikato Environment for Knowledge Analysis) incorporates a large number of
154 standard Machine Learning Techniques (ML) including the methods described above in a freely available tool (Frank et
155 al., 2016). With it, a specialist in a particular field is able to use ML to derive useful knowledge from databases that are
156 far too large to be analysed by hand. The workbench can either be used through a supplied Graphical User Interface, or

157 incorporated directly in Java code using a supplied library. All experiments described here are conducted using Weka
158 version 3-6-13. The three models used are described below. The NN and RF can be both be trained as classifiers, i.e.
159 predicting a class value (damaged/no damage) or to undertake regression, i.e. output a continuous value. We did not
160 attempt any model tuning in order to determine how well the WEKA software performed “off the shelf”.

161

162 2.3.1. Artificial Neural Network

163 The *artificial neural network* contains an input layer consisting of n neurons, each corresponding to one of the selected
164 inputs variables. In classification mode, the output layer contains two neurons, one indicating the positive class, and the
165 other the negative class. When used for regression, there is a single output neuron. In addition, there is a single hidden
166 layer consisting of $(\text{inputs}+\text{outputs})/2$ neurons. Each neuron receives a weighted sum of inputs $x = \sum_{i=1}^k w_i v_i$, where $v_i =$
167 the value of the input and w_i the weight connecting the input to the neuron, and outputs a value $s(x)$ using a sigmoid
168 activation function as defined in Eq. 1:

169

$$170 \quad s(x) = \frac{1}{1+e^{-cx}} \quad (1)$$

171

172 Weights are initialised at random and the *backpropagation* algorithm used to find a set of weights that minimizes the
173 total error at the outputs, summed over all input records:

174

$$175 \quad E = \frac{1}{2} \sum_{i=1}^p \| o_i - t_i \|^2 \quad (2)$$

176

177 Backpropagation is a gradient descent technique that modifies each weight in small steps based on the gradient of the
178 error function with respect to the weight concerned, e.g.

179

$$180 \quad w_n = w_n - \eta \frac{\delta E}{\delta w_n} \quad (3)$$

181

182 where w_n is the total error calculated at each step. The learning rate η is an adjustable parameter that modifies the step
183 size, but was set to 0.3 in all our experiments. An additional *momentum* term is used that enables the gradient descent
184 algorithm to escape from local minima, and is set to a default value of 0.2. Backpropagation is applied for a fixed number
185 of 500 iterations for each model. These represent the default settings in the WEKA software.

186

187 2.3.2. Random Forests

188 The *Random Forests* algorithm uses a bagging approach, combined with a Random Tree learning algorithm. In bagging,
189 multiple random subsets of the dataset are created by sampling n instances with replacement from the dataset. For each
190 subset, a random tree classifier is grown: at each node, m variables are selected at random, from which the one that
191 optimizes the information gain is chosen. We use the default Weka parameters: a forest of 100 random trees are created;
192 each tree has unlimited depth and is grown without pruning; at each node $m = \log_2(\text{number_of_attributes}) + 1$ are
193 randomly selected.

194

195 2.3.3. Logistic Regression

196 *Logistic regression* estimates the probability of a binary response variable based on the set of predictor inputs. The Weka
197 implementation of the multinomial logistic regression model with a ridge estimator is loosely based on the description
198 given by Le Cessie and Van Houwelingen (1992).

199

200 Given k classes, and n instances with m attributes, an $m^*(k-1)$ parameter matrix β is calculated. The probability of class i
201 is given by Eq. 4 where Y_i are the mutually independent response variables (1,0), $p(X_i)$ is the probability that $Y_i = 1$, and
202 X_i are the m -dimensional rows of covariates.

203

$$204 \quad p(X_i) = \frac{\exp(X_i\beta)}{\{1+\exp(X_i\beta)\}} \quad (4)$$

205

206 The log likelihood is given by Eq. 5. A ridge estimator is used to improve the parameter estimates and diminish the error
207 made by further prediction. In order to find the matrix β for which l is minimised, a Quasi-Newton Method is used to
208 search for the optimized values of the $m^*(k-1)$ variables. Before Weka runs the optimization procedure, the matrix β is
209 compressed into a $m^*(k-1)$ vector. The default Weka parameter for the ridge estimator λ of 1×10^{-8} is used.

210

$$211 \quad l = \sum_i [Y_i \log(p(X_i)) + (1 - Y_i) \log\{1 - p(X_i)\}] + \lambda * \beta^2 \quad (5)$$

212 2.3.4. Models

213 We evaluate the models above with respect to two functions:

214

- 215 • Damage Prediction: We adopted a dichotomous model which predicts damage at the level of individual trees in
216 two categories, damaged or undamaged. A separate model was trained for each of the two data sets. For each of
217 the three classification methods described, the default parameters supplied with Weka were used to train the
218 model.
- 219 • Critical Wind Speed Prediction: A linear regression model (LIN) was used instead of the logistic regression model
220 (LOG) because it is more appropriate for a variable output (non-dichotomous). All models (LIN, NN, RF) were
221 trained to predict critical wind speeds for breakage and overturning at tree level using values obtained from
222 running a GALES simulation as training data (see 2.4.1 below). The variables used to train the models are given
223 in Table 1.

224

225 *2.3.5. Training and Pre-Processing*

226 Cross-validation is used to obtain an unbiased estimate of the performance of each model on unseen test data. For each
227 model, the dataset is randomly divided into 10 subsets (folds) of equal size. 9 folds are combined to train a model, with
228 the left-out fold used for testing the trained model. The procedure is repeated leaving each of the 10 folds out in turn. The
229 final reported accuracy is the average of the accuracy value obtained on each of the 10 folds.

230

231 For damage prediction, given that the data is unbalanced in terms of the ratio of damaged/undamaged trees, it is
232 preferable to bias the data used to train the models towards a uniform class distribution. The Weka *SpreadSubsample*
233 filter is applied to the subset of data used in each training fold during cross-validation: this produces a new dataset twice
234 the size of the minority class, by selecting all instances of the minority class (damaged tree in this case) and randomly
235 sampling from the majority class (undamaged trees in this case). In order to eliminate variability due to the effects of
236 random sampling in this way, 10 new data-sets were created as just described. All models are trained and tested as
237 described above using each sub-sampled data-set, with mean results, standard deviations and/or boxplots used to report
238 findings.

239

240 *2.3.6. Outputs from each model*

241

242 *Damage-prediction models:* For the NN, Weka returns a probability distribution based on the outputs from the network
243 defining the probability of a tree being damaged, for each input vector. The discrimination threshold is set at 0.5, such

244 that a probability of greater than or equal to 0.5 results in the tree being classified as damaged. The same threshold is
245 used with the LOG and the RF models. No adjustment of this threshold was made in order to determine how well the
246 models performed without any tuning.

247

248 *Critical wind-speed models:* the LIN, NN and RF models output a single real-valued number for the critical wind speed
249 for breakage and a single real-valued number for the critical wind speed for overturning.

250

251 2.3.7. Performance Metrics

252 For the dichotomous models, we record *classification accuracy*, i.e. the proportion of true results (both true positives and
253 true negatives) among the total number of cases examined. In addition, we report the area underneath the receiver-
254 operating curve (AUC). This plots the false positive rate against the false negative rate: a perfect classifier would have an
255 AUC of 1.0; an area of 0.5 is equivalent to random guessing. Typically, an $AUC > 0.7$ is considered to be *fair*, above 0.8
256 *good* and above 0.9 to be *excellent* (Hosmer and Lemeshow, 2000).

257

258 For prediction of numeric values (i.e. critical wind speed) the correlation coefficient is reported. All statistics were either
259 calculated within the WEKA software or with Matlab 2016a (Mathworks, Natick MA, USA).

260

261 2.4. GALES

262 GALES is a hybrid mechanistic model for predicting the critical wind speeds (CWS) for damage to forest stands and
263 trees due to overturning and breakage and is designated a CWS model in the convention adopted by Gardiner et al.
264 (2008). If wind climate data is available then the probability of such wind speeds being exceeded and damage occurring
265 is also calculated, and this version of the model is called ForestGALES and is designated a Wind Risk Management tool
266 (WRM) using the same designation system. GALES requires information on the tree species, tree diameter at breast
267 height (*DBH*), tree height, stand mean tree diameter at breast height (DBH_{mean}), stand mean tree height, mean stand
268 spacing, soil type and rooting depth. Although GALES calculates the CWS for both stem breakage and overturning
269 (uprooting), in this paper the CWS used in damage model development is always the minimum of the two, i.e. the most
270 likely to occur and we did not attempt to discriminate between damage types.

271

272 Full details of the model and its validation can be found in Gardiner et al. (2000) and Hale et al. (2015). The parameters
273 in GALES used for maritime pine stands are given in Cucchi et al. (2005).

274

275 *2.4.1. GALES artificial training dataset*

276

277 A large number of potential maritime pine stands with characteristics that covered the full range of possible
278 characteristics (see Table 1 for details of the ranges sampled) were created as inputs to GALES. The stand characteristics
279 were selected using Latin Hyper Cube Sampling to give uniform sampling. 10,000 stands were created, which after
280 filtering for duplicates, constraining the ratio of stand mean tree height to stand mean *DBH* between 30 (very high taper)
281 and 130 (very low taper), and constraining individual tree *DBH* and height to be within $\pm 70\%$ of the stand mean values,
282 left 1970 simulations.

283

284 GALES was then run for the 1970 stands and the CWS values for tree overturning and stem breakage were calculated at
285 10 m above the zero-plane displacement ($d+10m$), which is the standard height for such measurements in Gardiner et al.
286 (2000) and at 29m and 40m above the ground, which correspond to the maximum tree heights in the Nezer Forest and in
287 the whole of the NFI data set respectively (Kamimura et al., 2016).

288

289 The outputs from the GALES runs were then used to train LIN, NN and RF models to predict CWS for overturning and
290 breakage at $d+10$ m, 29 m and 40 m. The trained models were finally tested by comparing their predictions of CWS
291 against GALES calculated CWS at $d+10$ m and 29 m for the Nezer Forest and at $d+10$ m and 40 m for the NFI data (see
292 Part 1 in Fig. 1).

293

294 *2.5. WAsP predicted wind speeds*

295 The Wind Atlas Analysis and Application Program (WAsP) (Mortensen et al., 1993) was used to estimate the wind
296 speeds above the forest during the Martin and Klaus storms. A land-use map (elevation range, 0 to 300 m; contour
297 interval = 50 m) plus an aerodynamic roughness map (water = 0.003 m; unforested areas = 0.01 m; forest = 1.0 m) was
298 used in the simulations. The input wind speeds for WAsP were taken from the coastal meteorological station at Cap
299 Ferret (approximately 25 km north-west of the Nezer Forest at 44°38'N, 1°15'W). Wind speeds were simulated at a
300 horizontal resolution of 500 x 500 m, at a height of 29 m (just above height of tallest trees in the Nezer Forest) for storm

301 Martin, and at heights of 29 and 40 m (just above height of tallest trees in the NFI data) for storm Klaus. Full details are
302 given in Kamimura et al. (2016).

303

304 2.6. Data

305 2.6.1. Study site and data

306

307 The field data used in this study are the same data as used in Kamimura et al. (2016). There are two groups of data. The
308 first is from a field survey of 29 permanent plots ($400\text{m}^2 \cdot \text{plot}^{-1}$) in the Nezer Forest, located in Nouvelle-Aquitaine
309 region ($44^\circ 34' 20''\text{N}$, $1^\circ 2' 20''\text{W}$). Tree size was surveyed in 1998, and damaged trees were determined after storm
310 Martin in 1999 (Table 2). Data consist of tree height, stem diameter at breast height (*DBH*, 1.3 m), tree location, and
311 damage status for most trees. The data was not sub-divided as was the case in Kamimura et al. (2016). The second data
312 set was from field surveys of the National Forest Inventory in France (Inventaire Forestier National; NFI, (Robert et al.,
313 2009)) in the same region, which is predominately maritime pine stands. The annual survey plots (1 point for 10 km^2) are
314 chosen in a systematic sub-sample of the 5-year sample covering the entire country. The forest field plots are composed
315 of four concentric plots allowing the measurement of different tree diameter classes (Robert et al., 2009). We used data
316 collected from 2007 to 2008 from a total of 235 plots chosen in two ecological regions of the Landes de Gascogne Forest,
317 and wherever more than half of the trees in each plot were maritime pine. After storm Klaus in 2009, damaged trees in
318 the NFI plots were identified by an additional follow up field survey to list damaged trees (Table 2). For each plot in the
319 two data sets we added mean plot height, the mean plot *DBH* and the average stem spacing derived from the individual
320 tree data. Spatial information included the distance of each tree from the windward stand edge (west) and the upwind gap
321 size (distance in a westerly direction between the forest and the next forest block) were also estimated based on the
322 position of the inventory plot (only accurate to within 500m). However, in this paper we assumed like Kamimura et al.
323 (2016) that all the trees were effectively at a new edge because the best results were previously found with this
324 assumption. This assumption is justified by the observation from aerial photography that damage propagated through
325 stands during the storms and this led to new trees becoming exposed to an advancing damaged forest edge. The NFI plots
326 were identified either within the Landes (main forest production area inland from the coast) or Dunes (forest along
327 coastal dunes) areas based on the ecological region given in the NFI survey, whereas all the plots in the Nezer Forest were
328 designated as Landes. Soil characteristics and hydrological status were derived from the French soils database (GISsol,
329 2011) and the ecological observations in the NFI plots (Bruno and Bartoli, 2001). Soils are mainly sandy podzols and

330 arenosols, respectively in the Landes and in the Dunes areas. Gleys and brown soils are also present but only in the
 331 Landes area. In the Nezer Forest the soils are hydromorphic podzols, and their dominant hydrological status is "slightly
 332 wet". Soil depth is greater in the Dunes and Landes area with a dry hydrological status than in those Landes areas with a
 333 wetter hydrological status. An outline of the data used in the development of the models is provided in Table 3.

334

335 Full details of the data and the calculation of derived parameters is provided in Kamimura et al. (2016) and the location
 336 of the forests and the individual sample plots is given in Fig. 1 of Kamimura et al. (2016).

337

338 Table 1: Characteristics of the data set used to train the LIN, NN and RF models to simulate GALEs critical wind speed
 339 predictions for maritime pine

<i>Model Variable</i>	<i>Mean Value</i>	<i>Range</i>	<i>Comment</i>
Soil	3	None	Fixed as <i>podzol</i>
Rooting	2	None	Fixed as Deep rooting ≥ 80 cm
Upwind gap width (m)	245.6	0-500	When gap = 0m then tree is effectively inside forest
Position relative to edge (m)	0	None	Fixed to always be at stand edge
Tree DBH (cm)	41.9	2.5-110	
Tree Height (m)	23.6	2.5-40	40 m is just above the maximum tree height of maritime pine in Landes de Gascogne Forest
Tree taper (m/m)	23.6	30-130	Constrained between 30 and 130 so trees not too thin or too tapered
Stand DBH (cm)	43.9	5-65	
Stand height (m)	24.8	2.5-35	
Stand taper (m/m)	60.9	30-130	Constrained between 30 and 130 so trees not too thin or too tapered
Tree DBH/Stand DBH	0.98	0.3-1.7	Constrained that tree size is within range $\pm 70\%$ of stand size
Tree height/Stand height	0.98	0.3-1.7	Constrained that tree size is within range $\pm 70\%$ of stand size
Stand density (trees/ha)	1840	30-3600	

340

341 Table 2: Levels of damage in the Nezer Forest and within the NFI database.

<i>Data</i>	<i>Number of Trees</i>	<i>% Damaged</i>	<i>% Undamaged</i>
Nezer Forest	1080	12% (134 trees)	88% (946 trees)
NFI	1705	33% (566 trees)	67% (1139 trees)

342

343

344 Table 3: Parameters and their range and standard deviation used in the model development for Nezer Forest and the NFI
 345 database. *DBH* is diameter at breast height (1.3m above ground) and *CI_BAL* is a competition index based on the basal
 346 area of all trees larger than the subject tree (Biging and Dobbertin, 1995)

<i>Model Variable</i>	<i>NFI: Range (Stdev)</i>	<i>Nezer Forest: Range (Stdev)</i>
Gap size (m)	41-328.2 (66.7)	28.4-262.5 (66.4)
Stand Mean DBH (cm)	8.0-65.1 (12.9)	3.9-43.4 (10.6)
Stand Mean Height (m)	4.1-32.8 (6.7)	2.8-26.3 (6.4)
Stand Density (ha)	28.3-2740.7 (399.7)	200-3594 (676.1)
Stand Mean <i>CI_BAL</i>	0.00-57.9 (9.7)	1.1-19.6 (6.6)
Tree DBH (cm)	7.6-111.00 (14.4)	2.5-61.0 (11.3)
Tree Height (m)	3.60-38.60 (6.9)	2.3-26.7 (6.6)
Tree <i>CI_BAL</i>	0.00-270.7 (18.1)	0.00-35.9 (9.7)
Distance from Edge (m)	0	0
CWS Breakage at d+10m GALES (ms ⁻¹)	10.9-45.4 (5.8)	12.7-46.2 (8.0)
CWS Overturning at d+10m GALES (ms ⁻¹)	10.0-32.5 (5.2)	11.3-40.0 (7.2)
CWS Breakage at 29m GALES (ms ⁻¹)	16.0-58.8 (5.5)	24.3-60.8 (7.6)
CWS Overturning at 29m GALES (ms ⁻¹)	13.7-48.2 (5.1)	25.0-53.7 (6.7)
CWS Breakage at 40m GALES (ms ⁻¹)	20.3-63.6 (5.8)	Not calculated
CWS Overturning at 40m GALES (ms ⁻¹)	18.8-52.2 (5.3)	Not calculated
WAsP predicted wind speeds at 29m (ms ⁻¹)	21-42 (4.5)	26.2-31.8 (1.8)
WAsP predicted wind speeds at 40m (ms ⁻¹)	24-43 (4.4)	Not calculated
Soil (1=Arenosol, 2=brown soils, 3=podzol, 4=gleys)	1-4	3
Hydro (1=very wet, 2=slightly wet, 3=dry)	1-3	2
Dune (1=Dune area, 0 = Landes area)	0-1	0

347

348 3. Results

349 3.1. Predicting CWS

350 The LIN, NN and RF model simulations of CWS were compared to the actual CWS produced by GALES for the Nezer
 351 and NFI data at 29 m and 40 m above the ground respectively, and are displayed in Table 4. Information for predictions
 352 at *d*+10 m can be found in Table A1 in Appendix A.

353 Table 4: Results of comparison of predictions from the trained LIN/NN/RF models and GALES for Nezer at 29 m and
 354 NFI data at 40 m. Numbers are correlation coefficient between trained model results and GALES predictions and root-
 355 mean square (RMS) error is given in brackets in ms⁻¹.

<i>Training Set</i>	<i>Test Set</i>	<i>Output</i>	<i>LIN</i>	<i>NN</i>	<i>RF</i>
GALES 29 m predictions from artificial data	Nezer	CWS for breakage	0.8836 (6.4165)	0.9251 (10.2185)	0.9137 (6.5713)
GALES 29 m predictions from artificial data	Nezer	CWS for overturning	0.9131 (3.0748)	0.9516 (3.838)	0.9394 (4.6022)
GALES 40 m predictions from artificial data	NFI	CWS for breakage	0.7659 (6.0699)	0.8565 (4.8805)	0.8437 (4.6879)
GALES 40 m predictions from artificial data	NFI	CWS for overturning	0.8264 (3.6150)	0.9347 (3.398)	0.9004 (2.8682)

356

357 The results show a high level of correlation between the predictions of GALES and those of the models. In all cases the
358 models are correlated to the GALES predictions with r^2 values greater than 0.77 and in most cases above 0.9. In all cases
359 the predictions of breakage are slightly less well correlated than the predictions of overturning. This might be a reflection
360 of the fact that only approximately 15% of trees were damaged by breakage during the two storms (trees in the Landes de
361 Gascogne Forest are more susceptible to overturning), and the models are consequently better trained to predict
362 overturning than breakage (more examples of overturning). In all cases the LIN models perform least well, the RF second
363 best and the NN performs best (average correlations of 0.847, 0.899 and 0.917 respectively). However, the RMS errors in
364 the predictions are quite large with values ranging between 2.87 to 10.22 ms^{-1} , and with an average value of 5.02 ms^{-1} .
365 This suggests that such models can be used for predictions for multiple trees and forest stands over large areas but not for
366 precise predictions for a small number of trees or individual stands. Overall the models appear better at predicting the
367 CWS at $d+10$ m rather than at fixed heights with r^2 values greater than 0.94 (see Table A1 in Appendix A). This is
368 probably due to the fact that $d+10$ m is at a relatively consistent height above the modelled trees (<10 m), whereas with
369 the fixed height values of 29 and 40 m the distance from the top of the trees to the calculation height is much more
370 variable (22.5 to 37.5 m).

371

372 A large advantage was obtained in computational efficiency. The GALES model used in this paper required 0.37 ms to
373 calculate the CWS for damage of a single tree using already known tree characteristics, whereas the LIN and NN derived
374 models only required 0.013 ms per tree. This represents a 28 times increase in calculation speed. The RF derived CWS
375 model required 0.065 ms per tree, a calculation speed more than 5.7 times faster than GALES. In the GALES version of
376 Gardiner et al. (2000) there is an iterative solution for calculating the additional moment provided by the overhanging
377 displaced mass of the canopy during a storm (Neild and Wood, 1999), whereas in in this paper we used a simple
378 analytical bending equation (Gardiner, 1992). Additional simulations showed that a further computational efficiency of a
379 factor of 2 would be obtained over the more complicated version of GALES. All calculations were based on 10 runs for
380 all 1705 trees in the NFI data set using a MathCad program (PTC, Needham, United States) on a Dell Latitude[®] laptop
381 (Dell, Round Rock, United States) running at 2.1 GHz (4 CPUs) with 16.0 GB of memory.

382

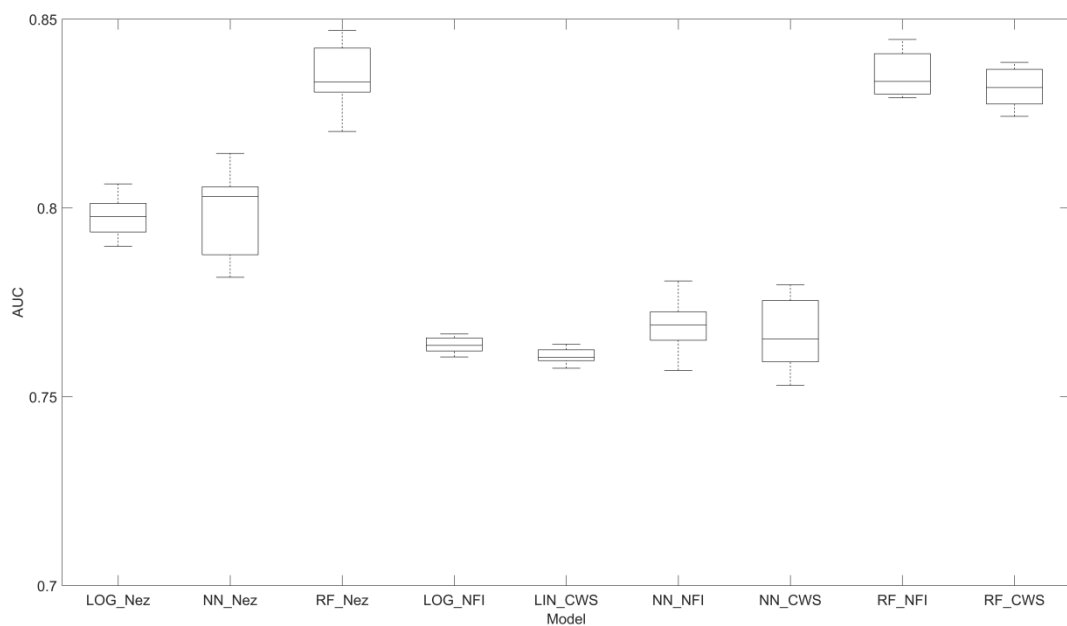
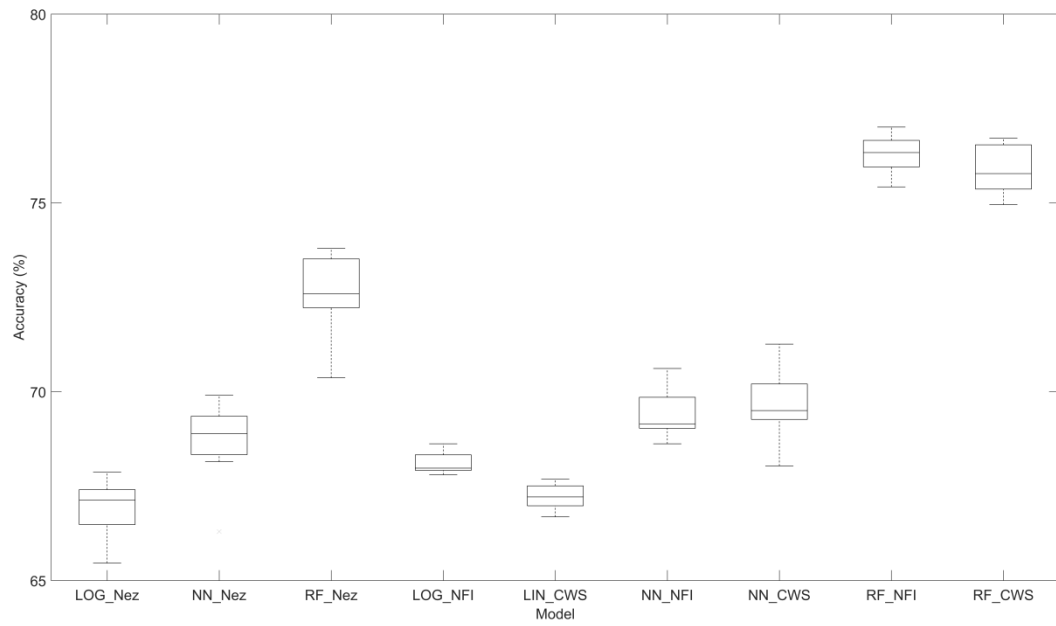
383 3.2. Wind damage to individual trees

384 3.2.1. Nezer Forest

385 In Fig. 2 the performance of the three damage modelling approaches (LOG/NN/RF) in predicting damage or no damage
386 for the Nezer Forest is illustrated (LOG_Nez, NN_Nez, RF_Nez). All the parameters in Table 3 were used with the
387 GALES CWS and WAsP wind speed calculated at 29 m. The accuracy and AUC values are given in the *All Variables*
388 column (indicating all possible variables used) in Table 5 and Table 6 respectively. The accuracy of the three models are
389 all reasonably good ($\geq 67\%$) but the NN model has a significantly higher accuracy than the LOG model with a value of
390 68.7% and the RF model has a statistically significantly higher accuracy than both other models with a value of 72.5%.
391 All three models have high values of AUC (≥ 0.8), which indicate *good* discrimination between damaged and undamaged
392 trees (Hosmer and Lemeshow, 2000). The AUC values for all three models are higher than the value obtained by
393 Kamimura et al. (2016) for the Nezer Forest using logistic regression models (AUC = 0.76). However, the accuracies are
394 lower for the LOG and NN models in comparison to the earlier work, which had an accuracy of between 71.9-72.4% in
395 the Nezer Forest. However, in Kamimura et al. (2016) the model accuracy was optimized by adjusting the cut points for
396 the probability of damage between 0 and 1 until the true positive rate equalled the true negative rate (Hosmer and
397 Lemeshow, 2000). As described earlier, in this paper no model optimisation was performed and the cut point was fixed at
398 0.5 in order to determine model performance with no tuning.

399
400 The accuracy and AUC of the models for the same data but using the calculated critical wind speeds at $d+10$ m above the
401 ground are presented in Fig. A.1 and Tables A2 and A3 of Appendix A. The results are very similar to the results using
402 the CWS at 29 m and suggest that the height of CWS calculation is not especially critical and the inclusion of the WAsP
403 calculated wind speeds made little difference to the accuracy or discriminatory ability of the models.

404



405

406

407 Fig. 2: Accuracy and AUC for the LOG, NN and RF damage model predictions using all data tree, stand and site data and
 408 the GALES predicted CWSs at 29 m against the Nezer Forest data (LOG_Nez, NN_Nez, RF_Nez) and the GALES
 409 predicted CWSs at 40 m against the NFI damage data (LOG_NFI, NN_NFI, RF_NFI). In addition a comparison is made
 410 for the NFI data (LIN_CWS, NN_CWS, RF_CWS) using the CWS values derived (see Part 1 of Fig. 1) from the three
 411 CWS models (LIN, NN, RF) instead of the GALES values.
 412

413 3.2.2. NFI data (Landes de Gascogne Forest)

414 In Fig. 2 there is also the same analysis as presented for the Nezer Forest data but for the NFI data and using the GALES
 415 CWS and WAsP predicted wind speeds at 40 m (LOG_NFI, NN_NFI, RF_NFI). The values are tabulated in Table 5 and

416 Table 6. In addition the results using the model predicted CWSs calculated in Section 3.1 were also used (LIN_CWS,
417 NN_CWS, RF_CWS) in place of the GALES derived CWS. The accuracies of the LOG and NN models are very similar
418 to the logistic regression model of Kamimura et al. (2016) where the accuracy was 69.6% when the NFI data were used
419 (see Table 8 in Kamimura et al., 2016), but the RF model is significantly more accurate (76.3%). The discriminatory
420 behaviour of the LOG and NN models is also similar to the logistic regression model in Kamimura et al. (2016) with
421 AUC values close to 0.77 compared to their value of 0.74. However, the RF model shows superior discriminatory power
422 with an AUC value of 0.84. In the simulations using the model predicted CWSs in place of the GALES derived CWS
423 (LIN_CWS, NN_CWS, RF_CWS) the AUC values are unaffected and only the accuracy of the simulations using the
424 CWS derived from the linear regression model (LIN_CWS compared to LOG_NFI) showed a significant reduction
425 ($p=0.0164$).

426

427 The results for the NFI data using calculations at $d+10$ m and 29 m and are shown in Fig. A.2 and Fig. A3, and Tables A2
428 and A3 in appendix A. They are very similar to the results presented here.

429

430 3.2.3. Model Sensitivity to Individual Parameters

431 The effects of leaving out one variable at a time on the accuracy and AUC value of the models for the Nezer Forest using
432 the CWS and WAsP wind speed calculated at 29 m are given in Table 5 and Table 6 and plotted in Fig. A.4 of Appendix
433 A. For each variable removal the model was always retrained with the remaining variables. The model performance using
434 the CWS calculated at $d+10$ m are displayed in Fig. A.5 and tabulated in Tables A.2 and A.3 of Appendix A.

435

436 Variable removal only has an effect for the LOG model where the removal of stand density and mean stand *DBH* slightly
437 reduce the accuracy and the removal of stand density slightly reduces the AUC (all significant at the $p=0.05$ level).

438 However, for the NN and RF models the removal of no variable had a significant effect on either model accuracy or
439 AUC. Note that in all the Nezer Forest simulations removing *Dune*, *Hydro* and *Soil* have no impact because they each
440 only have a single value in this forest (Table 3).

441

442 The response of the models developed using the NFI data and the CWS and WAsP wind speed calculated at 40 m are
443 also tabulated in Table 5 and Table 6 and plotted in Fig. A.6 of Appendix A. The results for the model performance using
444 the CWS calculated at 29 m and $d+10$ m are displayed in Fig. A.7 and Fig. A.8 and Tables A.2 and A.3 of Appendix A.

445 Removal of *Stand_density*, *Dune* and *Hydro* reduces the accuracy and AUC of the LOG model and additionally the

446 removal of *Soil* and the WASP calculated wind speed reduces the AUC of the LOG model. The NN model is only
447 affected by the removal of *Hydro*, which reduces the AUC of the model. The RF model is not affected by the removal of
448 any variable.

449

450 Overall there is relatively little impact of parameter removal on model performance. The LOG model is the most
451 sensitive and the RF model almost completely insensitive. This is probably not surprising because of the way that the
452 LOG and NN models utilise all the available variables, whereas the RF model creates nodes at each of which m variables
453 are selected at random, from which the one that optimizes the information gain is chosen. Interestingly the removal of
454 information on whether in the Dune or Landes area (*Dune*), the hydrological state of the soil, and to a lesser extent the
455 soil type itself had an impact on the LOG and NN model developed using the NFI data. This suggests that this
456 information provides an improvement in discrimination between damage and no damage but, because these variables are
457 not strongly correlated to other variables, the models cannot create an equally effective alternative model when this
458 information is missing.

459

460 Table 5: Mean accuracy of different models with each model variable removed in turn. Standard deviation is given in brackets. * indicates value significantly different (p<0.05) from
 461 the value with using all variables. The superscript letters against the values in the *All Variables* column (a, b, or c) indicate whether there are significant differences between the
 462 models for that particular height of CWS calculation at the p=0.5 level.

<i>Data Set</i>	<i>Model</i>	<i>CWS Height</i>	<i>All Variables</i>	<i>Average CI_BAL</i>	<i>CI_BAL</i>	<i>Tree DBH</i>	<i>Stand Density</i>	<i>Dune</i>	<i>Gap Size</i>	<i>Hydro</i>	<i>Stand DBH</i>	<i>Soil</i>	<i>Stand Height</i>	<i>Tree Height</i>	<i>CWS Break</i>	<i>CWS Overturn</i>	<i>WAsP Wind Speed</i>	
Nezer	LOG	29 m	66.954 ^a (0.76)	67.287 (0.801)	67.065 (0.929)	67.000 (0.688)	65.028* (0.772)	66.954 (0.76)	66.954 (0.76)	66.954 (0.76)	65.593* (0.581)	66.954 (0.76)	66.954 (0.76)	67.435 (1.053)	66.944 (1.206)	67.102 (0.795)	66.213 (1.042)	
	NN		68.741 ^b (1.028)	68.019 (1.329)	67.88 (0.961)	67.991 (1.573)	68.463 (1.407)	68.000 (1.279)	67.991 (1.176)	68.000 (1.279)	68.000 (1.279)	68.565 (1.107)	68.000 (1.279)	68.019 (1.414)	68.074 (1.621)	69.75 (2.046)	68.639 (1.162)	67.278 (1.054)
	RF		72.528 ^c (1.02)	72.167 (1.164)	72.519 (0.801)	73.056 (1.011)	72.259 (0.83)	72.565 (0.903)	72.287 (0.952)	72.611 (0.704)	72.352 (0.783)	72.481 (0.877)	72.454 (0.836)	72.454 (0.836)	72.491 (0.918)	72.843 (0.95)	72.426 (0.864)	72.065 (0.924)
NFI	LOG	40 m	68.094 ^a (0.283)	67.894 (0.282)	68.158 (0.277)	68.258 (0.321)	67.232* (0.212)	66.780* (0.324)	68.094 (0.283)	67.120* (0.373)	68.188 (0.458)	67.918 (0.322)	68.094 (0.283)	67.648 (0.215)	68.106 (0.269)	67.988 (0.335)	67.877 (0.303)	
	NN		69.443 ^b (0.679)	69.238 (0.672)	69.959 (0.990)	70.006 (0.643)	69.484 (0.665)	69.496 (0.957)	69.543 (0.345)	68.528 (0.684)	68.979 (0.911)	68.686 (0.548)	69.138 (1.045)	69.736 (1.382)	69.865 (0.725)	69.460 (0.858)	69.056 (0.499)	
	RF		76.305 (0.466) ^c	75.701 (0.342)	76.587 (0.632)	76.493 (0.483)	75.900 (0.528)	76.534 (0.723)	76.076 (0.431)	75.742 (0.437)	76.082 (0.575)	76.328 (0.430)	76.100 (0.474)	76.100 (0.474)	76.211 (0.348)	76.217 (0.495)	76.416 (0.455)	75.672 (0.530)

463

464 Table 6: Mean AUC of different models with each model parameter removed in turn. Standard deviation is given in brackets. * indicates value significantly different (p<0.05) from
 465 the value with using all variables. The superscript letters against the values in the *All Variables* column (a, b, or c) indicate whether there are significant differences between the
 466 models for that particular height of CWS calculation at the p=0.5 level.

<i>Data Set</i>	<i>Model</i>	<i>CWS Height</i>	<i>All Variables</i>	<i>Average CI_BAL</i>	<i>CI_BAL</i>	<i>Tree DBH</i>	<i>Stand Density</i>	<i>Dune</i>	<i>Gap Size</i>	<i>Hydro</i>	<i>Stand DBH</i>	<i>Soil</i>	<i>Stand Height</i>	<i>Tree Height</i>	<i>CWS Break</i>	<i>CWS Overturn</i>	<i>WAsP Wind Speed</i>
Nezer	LOG	29 m	0.798 ^a (0.005)	0.8 (0.005)	0.799 (0.005)	0.8 (0.006)	0.78* (0.005)	0.798 (0.005)	0.798 (0.005)	0.798 (0.005)	0.793 (0.006)	0.798 (0.005)	0.798 (0.005)	0.803 (0.004)	0.793 (0.006)	0.798 (0.005)	0.8 (0.005)
	NN		0.799 ^a (0.011)	0.799 (0.012)	0.804 (0.01)	0.794 (0.011)	0.795 (0.015)	0.797 (0.013)	0.793 (0.012)	0.797 (0.013)	0.791 (0.021)	0.797 (0.013)	0.796 (0.011)	0.797 (0.011)	0.8 (0.01)	0.795 (0.011)	0.797 (0.013)
	RF		0.834 ^b (0.009)	0.834 (0.006)	0.832 (0.008)	0.839 (0.008)	0.835 (0.008)	0.837 (0.008)	0.837 (0.007)	0.836 (0.01)	0.836 (0.009)	0.835 (0.009)	0.836 (0.008)	0.836 (0.008)	0.832 (0.011)	0.837 (0.008)	0.836 (0.009)
NFI	LOG	40 m	0.764 ^a (0.002)	0.765 (0.002)	0.764 (0.002)	0.763 (0.002)	0.757* (0.002)	0.751* (0.002)	0.764 (0.002)	0.745* (0.002)	0.765 (0.002)	0.760* (0.002)	0.764 (0.002)	0.763 (0.002)	0.764 (0.002)	0.762 (0.002)	0.758* (0.002)
	NN		0.769 ^a (0.007)	0.766 (0.008)	0.771 (0.007)	0.773 (0.006)	0.767 (0.004)	0.767 (0.011)	0.765 (0.005)	0.749* (0.008)	0.765 (0.006)	0.759 (0.008)	0.764 (0.006)	0.769 (0.009)	0.772 (0.009)	0.768 (0.006)	0.764 (0.006)
	RF		0.836 ^b (0.006)	0.832 (0.006)	0.838 (0.005)	0.835 (0.005)	0.832 (0.005)	0.833 (0.006)	0.833 (0.005)	0.830 (0.005)	0.832 (0.007)	0.835 (0.005)	0.834 (0.006)	0.834 (0.006)	0.838 (0.006)	0.835 (0.006)	0.836 (0.006)

467 3.2.4. Model Sensitivity to Removal of Parameter Groups

468 The sensitivity of the models to the absence of groups of input variables was also tested. Four parameter groups were
469 defined as *Stand* = {*Gap Size*, *Stand Mean DBH*, *Stand Mean Height*, *Stand Density*, *Stand Mean CI_BAL*}; *Tree* = {*Tree*
470 *DBH*, *Tree Height*, *Tree CI_BAL*}, *Site* = {*WAsP 40m*, *Dune*, *Hydro*, *Soil*} and *CWS+WAsP* = {*CWS Breakage*, *CWS*
471 *Overturn*, *WAsP 40m*}. The results are illustrated in Fig. 3.

472

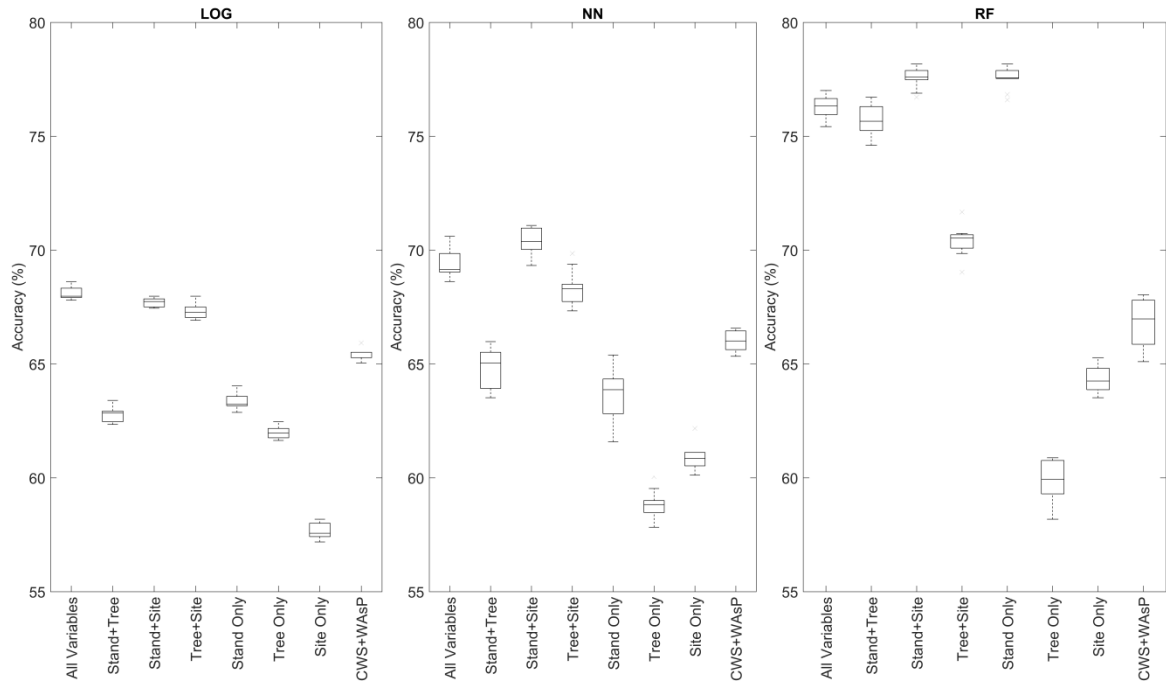
473 There are clear differences in the behaviour of the three models. The LOG and NN models are badly affected by the
474 removal of *Site* information and this was not compensated for by *Tree* or *Stand* information. *Site* information on its own
475 reduced the performance of both the models by a large and significant amount and this reflects the findings from the
476 single parameter removal in Section 3.2.3 that showed the LOG and NN models are sensitive to the removal of *Dune*,
477 *Hydro*, or *Soil* information. Removal of *Stand* information had a small but significant influence on the LOG and NN
478 models, but removal of just *Tree* information did not significantly affect the results. For the RF model the story is
479 different and the loss of *Stand* information is the most important factor. In fact *Stand* information on its own is enough to
480 produce high model accuracy and AUC values. In addition, the RF model results were slightly but significantly improved
481 when *Tree* level information was excluded. The *CWS+WAsP* information on its own provided reduced but reasonable
482 levels of accuracy and AUC for all models, and generally gave higher or equivalent results compared to any other single
483 parameter group (except *Stand* with the RF model) suggesting that the GALES model does provide a reasonable
484 assessment of damage risk in these forests.

485

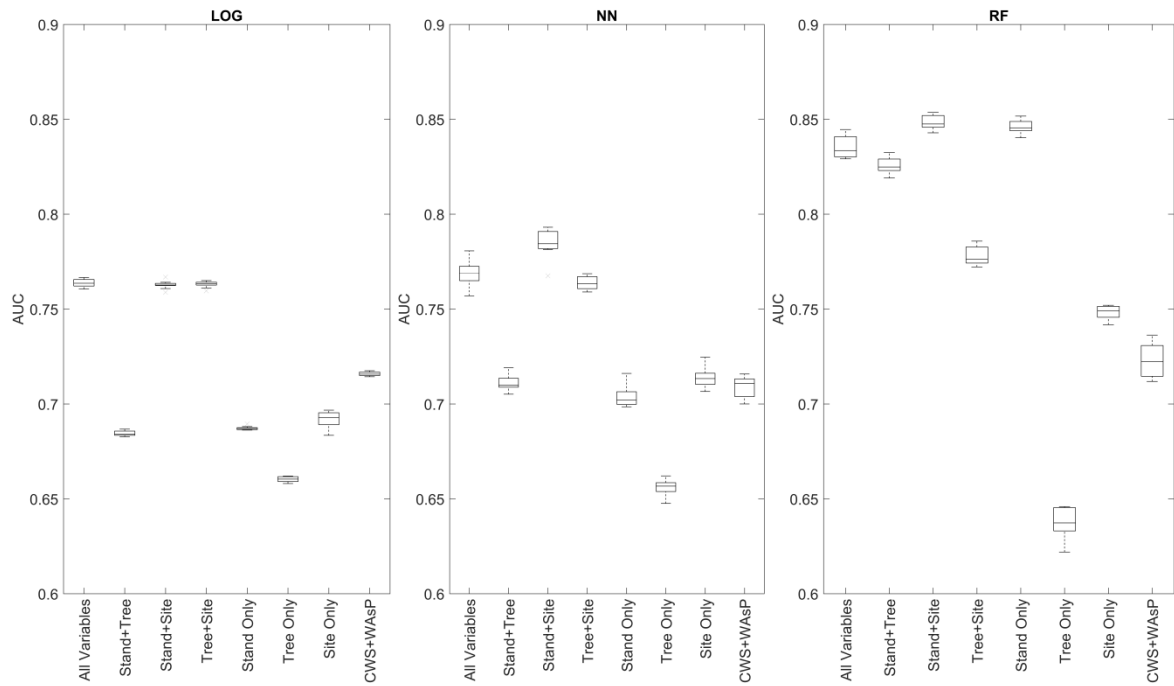
486 In summary, all models benefit from *Stand* level information and results are improved in particular by *Site* information
487 for the LOG and NN models. The LOG and NN models are unaffected and the RF model is slightly adversely affected by
488 the inclusion of *Tree* information and all models performed reasonably, but with reduced accuracy and discrimination,
489 when just the CWS values and the WAsP wind speed were used.

490

491



492



493 Fig. 3: Test of impact of leaving out different parameter groups in the damage models on the overall model accuracy and
 494 discriminatory ability (AUC) for the NFI data. *Stand* = {*Gap Size*, *Stand Mean DBH*, *Stand Mean Height*, *Stand Density*,
 495 *Stand Mean CI_BAL*}; *Tree* = {*Tree DBH*, *Tree Height*, *Tree CI_BAL*}, *Site* = {*WAsP 40m*, *Dune*, *Hydro*, *Soil*},
 496 *CWS+WAsP* = {*CWS Breakage*, *CWS Overturn*, *WAsP 40m*}. Note change of scales on the y-axes compared to Fig. 2.

497

498

499 3.2.5. Portability of models

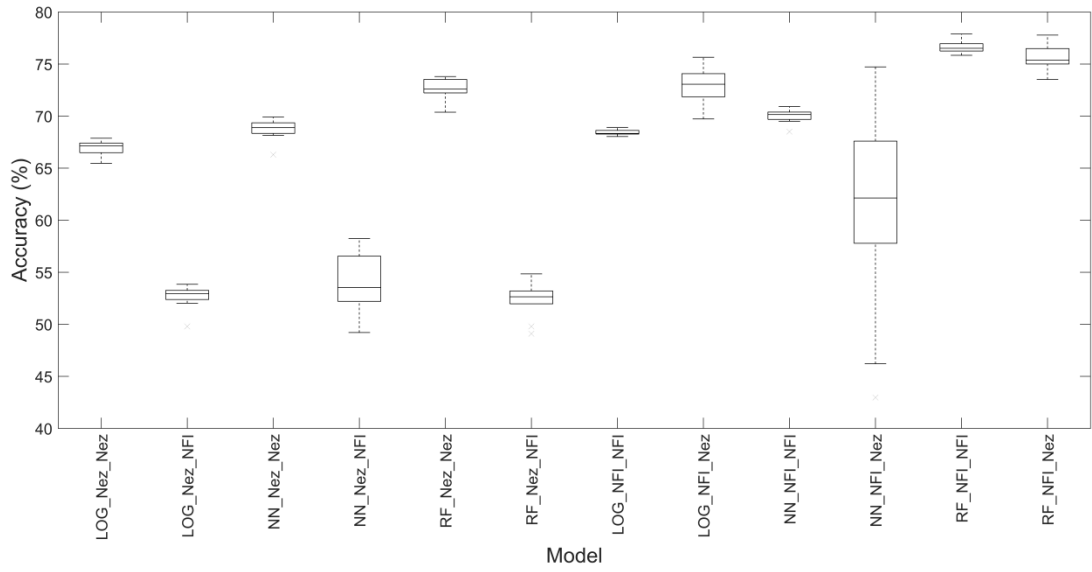
500 Model portability was tested by using the models developed from the Nezer Forest damage/no damage data and applying
501 them to the NFI damage/no damage data in the same manner as Kamimura et al. (2016). But in addition we also tested
502 the applicability of the NFI derived models on the smaller Nezer Forest data. In the same manner as discussed previously
503 (Sections 3.2.1 and 3.2.2) the test data was divided into 10 groups to allow 10 evaluations of model performance. Only
504 calculations using the CSW calculated at $d+10$ m and 29 m were used because calculations at 40 m were not available in
505 the Nezer Forest. The results are presented for the calculations at 29m in Fig. 4 and summarized for both heights in Table
506 A4 in Appendix A. It is clear from the results that there is a severe reduction in model accuracy and discriminatory ability
507 if the models developed on the Nezer Forest data (small forest area) are applied to the whole maritime pine forest estate
508 in the Landes de Gascogne Forest (NFI data). In fact the models all fail to provide accurate predictions (all values
509 between 50 and 55%) and have no discriminatory ability (AUC values close to 0.5). In the Nezer Forest there was a
510 limited range of tree sizes, and there was no variation in soil or hydrological properties and the whole area was classified
511 as a Landes ecological region. This meant there was no input data covering the larger range of conditions that exist in the
512 NFI data. However, the models developed with the much larger data set from across the whole Landes de Gascogne
513 Forest (NFI data) performed almost as well on the Nezer data set as when tested on the data from which it was originally
514 developed. In the case of the LOG model the performance appeared to be actually enhanced in terms of accuracy (see
515 Fig. 4 and compare LOG_NFI_NFI and LOG_NFI_Nez) although the difference was just not significant at the $p=0.05$
516 level ($p=0.0592$). The NN model had reduced accuracy and discriminatory ability (both significant at the $p=0.05$ level)
517 and the accuracy was very variable between the 10 tests. The RF model had no loss of accuracy but a reduction in
518 discriminatory ability (significant at $p=0.05$ level).

519

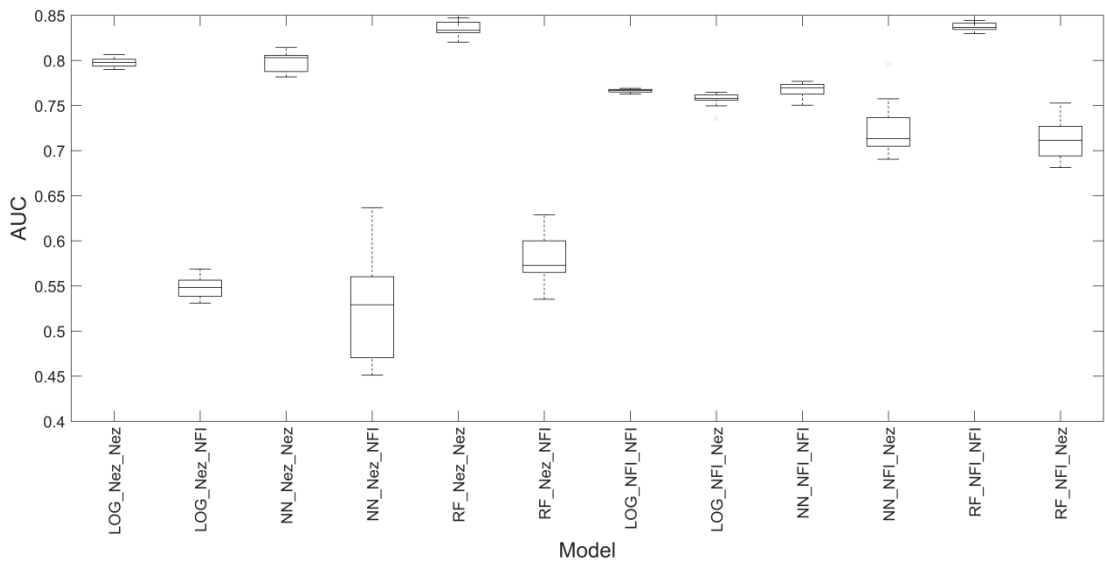
520 The results illustrate that the models developed from damage data in January 2009 (Storm Klaus) were able to
521 successfully predict damage from a previous storm in December 1999 (Storm Martin) when the state of the soil and
522 meteorological conditions were different. This suggests that such models, and especially the RF model, have the potential
523 for predicting damage risk to individual trees for future storms if developed on a comprehensive enough data set.
524 Unfortunately we have no other damage data sets with maritime pine on which to further test the models.

525

526



527



528 Fig. 4: Comparison of accuracy and AUC for predictions using the Nezer derived models on Nezer data (LOG_Nez_Nez,
529 NN_Nez_Nez, RF_Nez_Nez), using the Nezer derived models on NFI data (LOG_Nez_NFI, NN_Nez_NFI,
530 RF_Nez_NFI), NFI derived models on NFI data (LOG_NFI_NFI, NN_NFI_NFI, RF_NFI_NFI), and NFI derived
531 models on Nezer data (LOG_NFI_Nez, NN_NFI_Nez, RF_NFI_Nez). All calculations used the CWSs calculated from
532 GALES at 29m height.

533

534

535 **4. Discussion**

536 This paper follows on from the earlier work of Kamimura et al. (2016), which developed and tested the ability of logistic
537 regression model and the hybrid mechanistic model GALES to calculate individual maritime pine trees at risk of wind
538 damage in the Landes de Gascogne Forest of South-West France. That paper found good agreement of the predictions of
539 the GALES model against observed damage for specific conditions of soil and soil hydrological status, specifically
540 hydromorphic podzol, which was the only soil type on which tree pulling experiments in the region had been conducted
541 and the values from which had been used to parameterise the model (Cucchi et al., 2005). However, when the soil and
542 hydrological conditions changed the model had poor discrimination success between damaged and undamaged trees
543 (typically $AUC < 0.7$). The logistic model was able to simulate well the damage in the Nezer Forest and the region
544 represented by the NFI if the logistic model was calibrated for each forest area. However, the logistic model developed
545 for the Nezer Forest had no discriminatory ability when applied to the NFI forest area with a much larger range of
546 conditions. The logistic model was therefore not easily transferable even when the data from the NFI was filtered to only
547 investigate soil and hydrological conditions similar to the ones in the Nezer Forest, where the model had been developed
548 (Kamimura et al., 2016). This is a reflection of the fact that a model “trained” on a dataset with a limited range, and
549 which tries to minimise errors with that dataset, fails to produce satisfactory results when used with a dataset with a wider
550 range of characteristics (tree sizes, soil type, hydrological conditions, etc.)

551

552 In this paper we have attempted to determine whether other modelling approaches such as artificial neural networks and
553 random forests are able to perform more accurately and with greater discrimination than a logistic regression model or
554 the GALES model. In addition we wanted to determine if the models were more transferable from one area to another
555 than was previously found in Kamimura et al. (2016). The same data sets were used in this paper and the
556 parameterisation of the GALES model used in this paper to calculate critical wind speeds was identical to the previous
557 work. In addition to developing artificial neural network and random forests models we again developed a logistic
558 regression model for direct comparison with the previous work.

559

560 In addition, we wanted to determine if it was possible to substitute the hybrid-mechanistic model GALES by one of these
561 modelling approaches if they were previously “trained” using outputs from the GALES model run over a large range of
562 example stands. This could provide a very rapid method of calculating trees at risk over large areas such as the 790,000
563 ha of the Landes de Gascogne Forest or in computer simulations of different forest management scenarios such as have

564 been conducted in Finland by Zeng et al. (2007). This would allow near rapid simulations of alternative management
565 approaches for forest management planning and a very quick assessment of the impact of a plan on the current and future
566 wind damage risk to the forest.

567

568 All the models in conjunction with regional predictions of wind speed during storms Martin and Klaus were successful at
569 predicting individual tree damage within both the very well defined and measured Nezer Forest as well as across the
570 whole of Landes de Gascogne Forest. However, overall there was little improvement in the accuracy or discriminatory
571 ability of the artificial neural network model used in this study over the logistic regression model and results were similar
572 to those obtained in the previous study both for the Nezer Forest and with the NFI data. This is in contrast to Hanewinkel
573 et al. (2004) who found enhanced identification of damaged trees with the artificial neural network model compared to
574 the logistic regression model. However, we did find that the random forests model produced enhanced accuracy and
575 AUC values over all the other models for all circumstances (both forest test areas and for all heights of CWS calculation)
576 and showed *good* discriminatory power (AUC between 0.827 and 0.837).

577

578 The random forests models were also found to be extremely insensitive to removing any individual variable but
579 performance was adversely affected when all stand variables (*Gap Size, Stand Mean DBH, Stand Mean Height, Stand*
580 *Density, Stand Mean CI_BAL*) were removed. In contrast both the logistic regression and artificial neural network models
581 were more sensitive to the removal of individual variables and the logistic regression model particularly sensitive to the
582 removal of the information on whether the stand was in the Dune or Landes area, the soil type and its hydrological status
583 (*Dune, Soil* and *Hydro* variables). This was confirmed by the removal of groups of variables covering tree, stand and site
584 conditions where the logistic regression and artificial neural network models were very sensitive to the removal of all site
585 variables (*WAsP 40m, Dune, Hydro, Soil*), and performed best when site and stand information were available. These
586 observations support the previous findings of Kamimura et al. (2016) where the logistic regression model lost
587 discriminatory power if there was no information on whether the plot was in the Dune or Landes area, what the soil type
588 was, and the hydrological status of the soil.

589

590 Interestingly the removal of either individual tree variables or all tree variables (*Tree DBH, Tree Height, Tree CI_BAL*)
591 did not have a negative influence on any model performance and in fact there was a slight but significant improvement
592 for the random forests model. This may be a reflection of the data distribution for tree variables that make it harder for

593 the random forests method to find good unique values on which to split the data and build a good model. However, the
594 fact that all models were not affected by the lack of tree data might suggest that for severe storms in forests similar to the
595 Landes de Gascogne Forest the damage is controlled by stand and site characteristics and individual tree characteristics
596 do not control the effective vulnerability to the wind. This would fit with the accepted view of the nature of damage
597 within these forests, which is that it is triggered at vulnerable edges resulting from a recent clear-felling and then
598 propagates through the stand damaging almost all trees regardless of their individual characteristics (Dupont et al., 2015;
599 Kamimura et al., 2016).

600

601 All models were successful in replicating the outputs of the GALES model using the training data set with r^2 values, in
602 almost all cases, greater than 0.9 between predicted critical wind speeds and the GALES derived critical wind speeds.
603 This extremely strong correlation meant that substitution of model derived critical wind speeds for the GALES values in
604 the damage model predictions of damage/no damage had almost no impact. However, the use of the critical wind speeds
605 calculated by GALES or the CWS models as inputs for the damage models leads to concerns about error propagation.
606 Therefore, because the performance of all the damage models was unaffected by the removal of critical wind speeds as
607 inputs, it might be advisable to use damage models developed using only measured data. In addition, all the CWS models
608 had a large standard deviation in their predictions indicating that the model derived critical wind speeds would only be
609 appropriate for large areas and multiple simulations, such as investigating management options over a whole forest,
610 rather than in calculations for individual trees or stands. Another use would be to provide a starting (seed) wind speed in
611 the iterative calculations used in the GALES model itself (Hale et al., 2015).

612

613 The models developed with the large extensive data set across the whole of Landes de Gascogne Forest (NFI data)
614 following damage caused by Storm Klaus in 2009 were successful in predicting the damaged trees in the smaller Nezer
615 Forest for a completely different storm (Storm Martin in 1999). However, the models developed with the Nezer data
616 showed no predictive ability for the storm damage in the larger NFI data set. This agrees with the findings of Kamimura
617 et al. (2016), as discussed earlier, who were unable to successfully apply their logistic model developed with the Nezer
618 data to predict damage in the whole Landes de Gascogne Forest and it is no surprise that models developed within a
619 limited data set do not work in larger more complex areas.

620

621 Altogether the results suggest that the random forests modelling approach can very successfully predict the trees that will

622 be damaged during a storm with an accuracy of up to 76% so long as good quality data are available to “train” the model.
623 This data can be from any storm so long as there is a sufficient range of input conditions because the models were found
624 to be transferable to other storms under such conditions. The random forests model could also be used in large-scale
625 scenario testing to investigate different management options into the future. Such an approach would provide a powerful
626 planning and public engagement tool because the models are fast and the impact of decisions could be visualised almost
627 immediately.

628

629 **5. Conclusions**

630 The results from this investigation of new approaches to modelling forest wind damage suggest that artificial neural
631 networks are no better than logistic regression models in their accuracy or discriminatory ability in determining which
632 trees are likely to be damaged. However, no model tuning was employed with either approach so performance might be
633 improved with adjustment of parameters such as the damage cut point. Even so, the models based on the random forests
634 approach were found to be much more accurate and had higher discriminatory power than the logistic regression and
635 neural network models in all circumstances and to give high accuracy (>75%) and good discrimination (AUC>0.8). In
636 addition they were almost completely insensitive to the removal of any specific input variable and dependent on only
637 stand level information to achieve good results. This would mean that they could be used successfully even if specific
638 data were missing. Tree level information was found to be unimportant in all models suggesting that the dominant
639 damage mechanism in these forests is propagation of damage from vulnerable forest edges, which affects all trees
640 regardless of their size.

641

642 The random forests model along with the other approaches was also successfully able to predict the critical wind speeds
643 (CWSs) predicted by the GALEs model if trained on an extensive enough artificial data set. The models are much faster
644 than GALEs due to a lack of a requirement for iteration and so could be used for running large scale “what if” scenarios
645 as part of scenario modelling and testing or planning exercises involving stakeholders.

646

647 The models that were developed all require extensive data sets of actual damage (large range of input variable values) for
648 their development and could be transferred to other regions if the forest conditions in the new area are comprehensively
649 covered within the model training data set. However, if the conditions are different and no detailed damage data from

650 storms in the new area are available the models are unlikely to be transferable. In contrast, all the models can be trained
651 to replace GALES if a large artificial data set covering the range of stand characteristics to be found in the new region is
652 first used to “train” them and this could be extremely useful for large scale forest planning in any region that has its
653 specific conditions and species incorporated in the GALES model.

654 **Appendix A.**

655 Supplementary data can be found in Appendix A.
656

657 **Acknowledgements**

658 We are grateful to Thierry Bélouard (IGN) who kindly provided the national forest inventory data in the Landes de
659 Gascogne Forest (Projet CRA 2012 IGN-IDF-INRA), as well as to Gaston Courier and Didier Garrigou at INRA-
660 Bordeaux who conducted the field surveys in the Nezer Forest. This work was funded by an INRA scientific package
661 awarded to Barry Gardiner and by grant ANR-12-AGRO-0007-04 (ANR, Agrobiosphere, France, project “FOR-WIND”)
662 and developed out of work undertaken in grant EP/J021628/1 to Emma Hart (EPSRC, UK)

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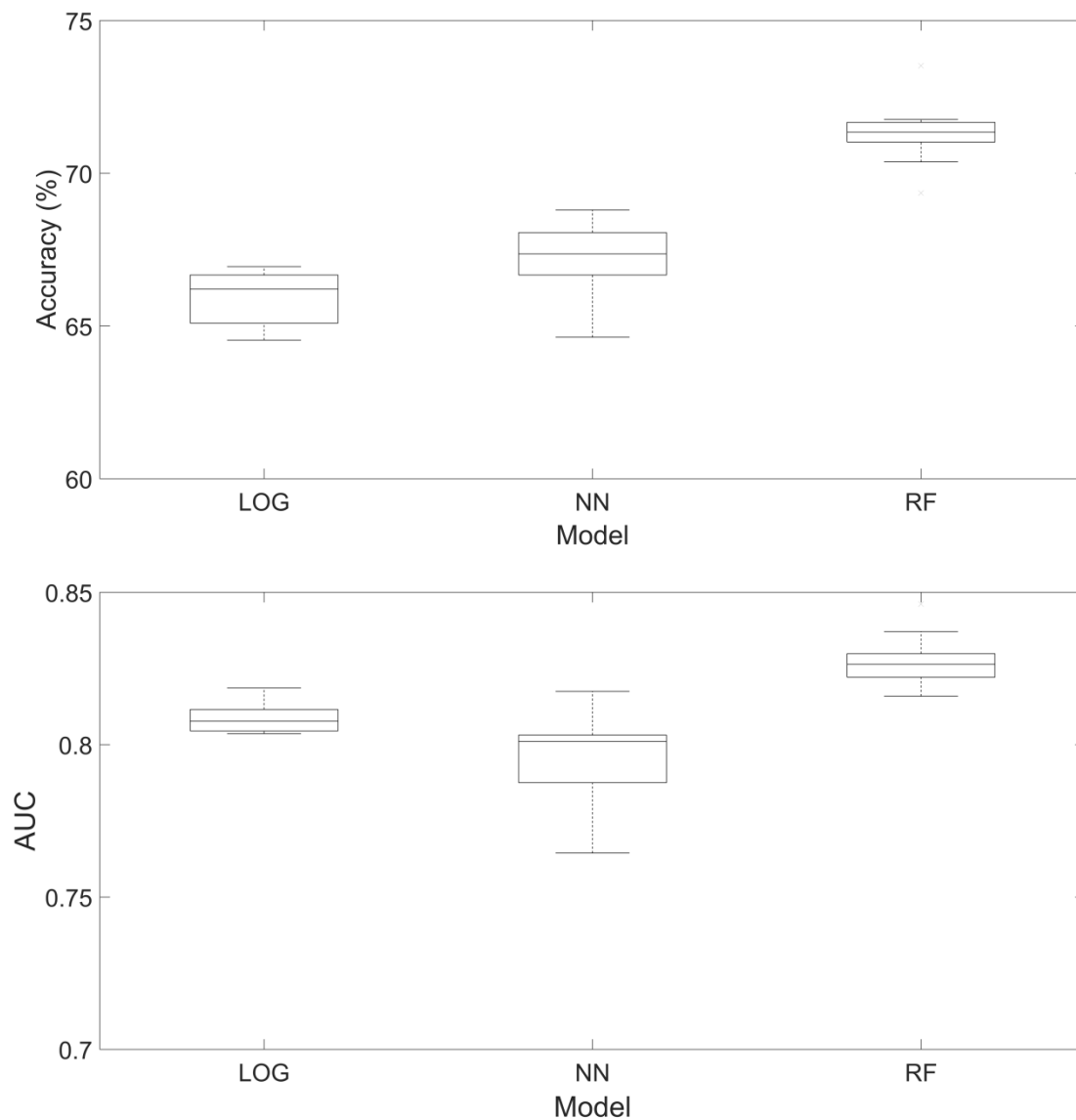
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759

1 Appendix A: Supplementary Material for “Use of Machine Learning
2 Techniques to Model Wind Damage to Forests”

3

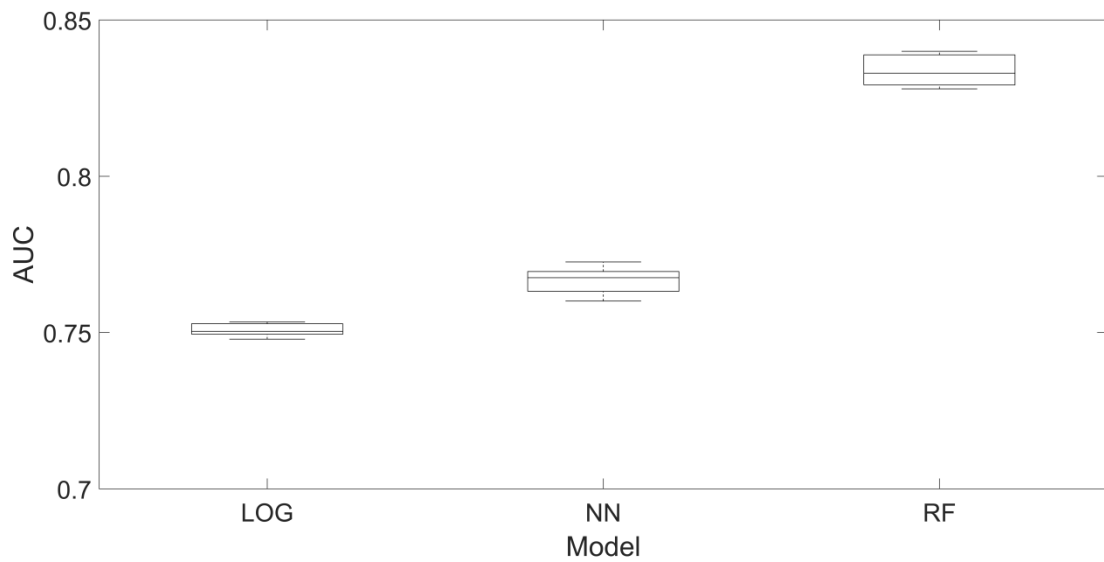
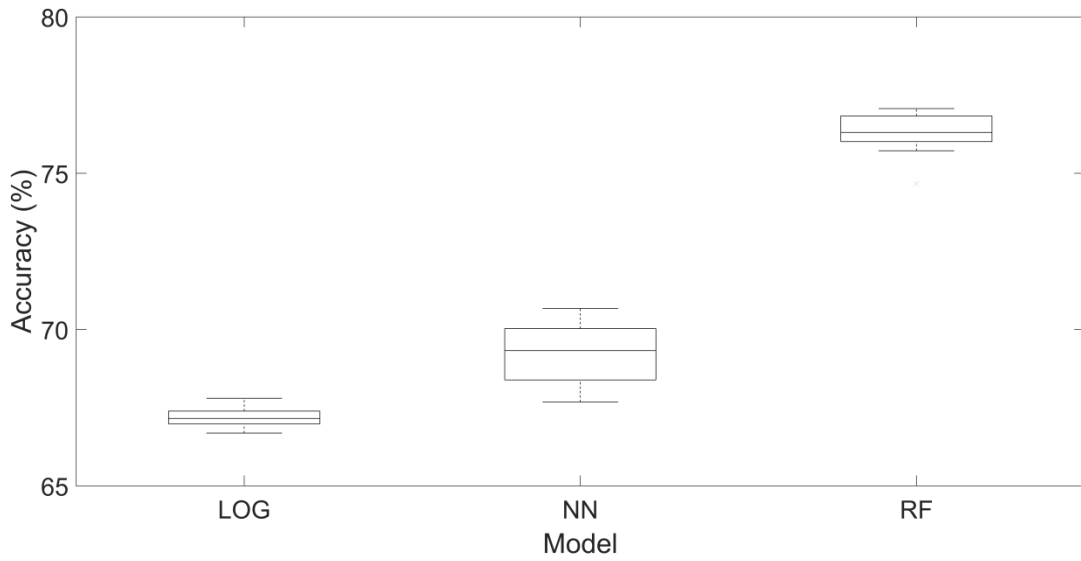


4

5

6 Fig. A 1: Accuracy and AUC for the LOG, NN and RF model predictions using the GALEs predicted CWSs at
7 $d+10$ m against the Nezer damage data. All variables in Table 3 were used except the WASP derived wind
8 speeds because these are only calculated at a single height above the ground and the $d+10$ m results are for
9 variable heights above the ground depending on the calculated value of d .

10

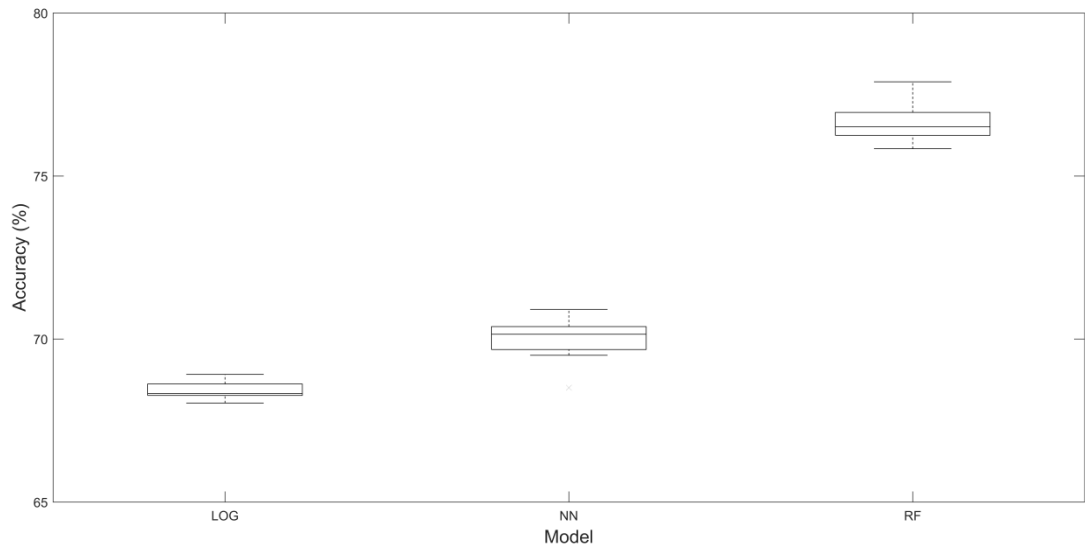


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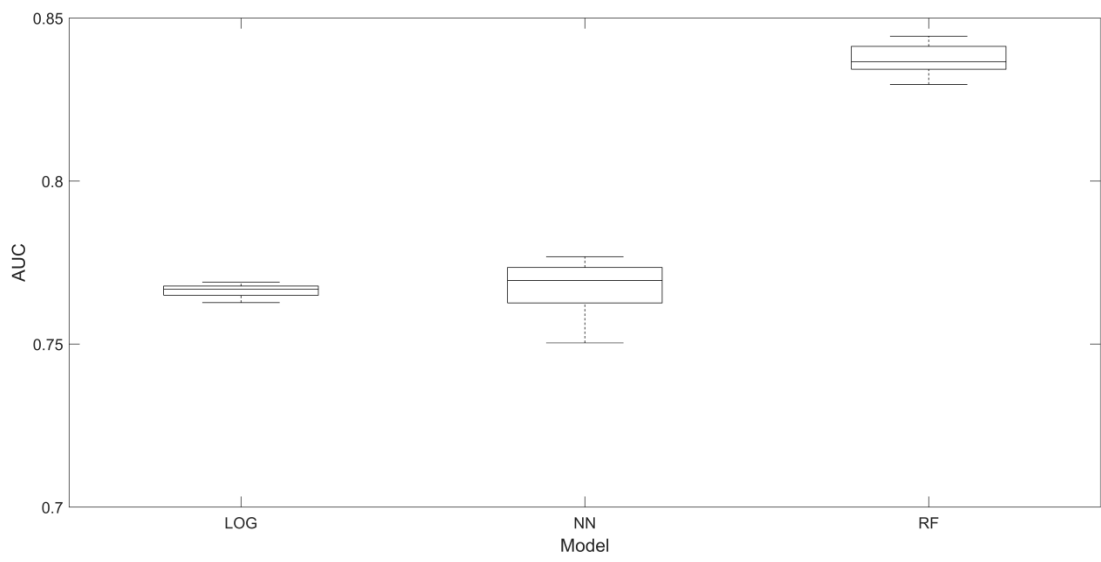
12

13 Fig. A 2: Accuracy and AUC for the LOG, NN and RF model predictions using the GALES predicted CWSs at
 14 $d+10$ m against the NFI damage data. All variables in Table 3 were used except the WASP derived wind speeds
 15 because these are only calculated at a single height above the ground and the $d+10$ m results are for variable
 16 heights above the ground depending on the calculated value of d .

17



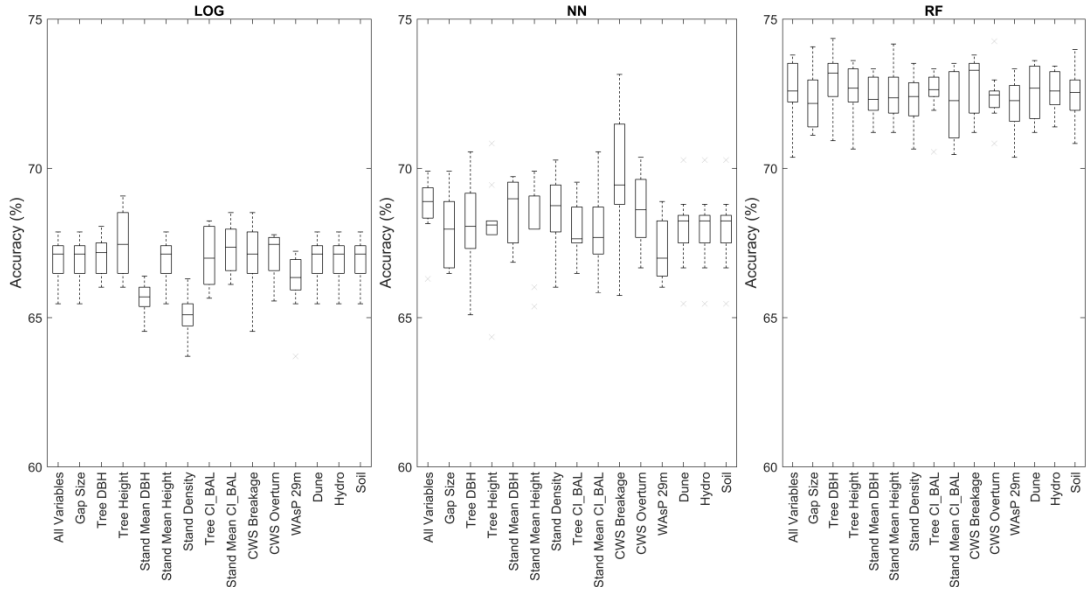
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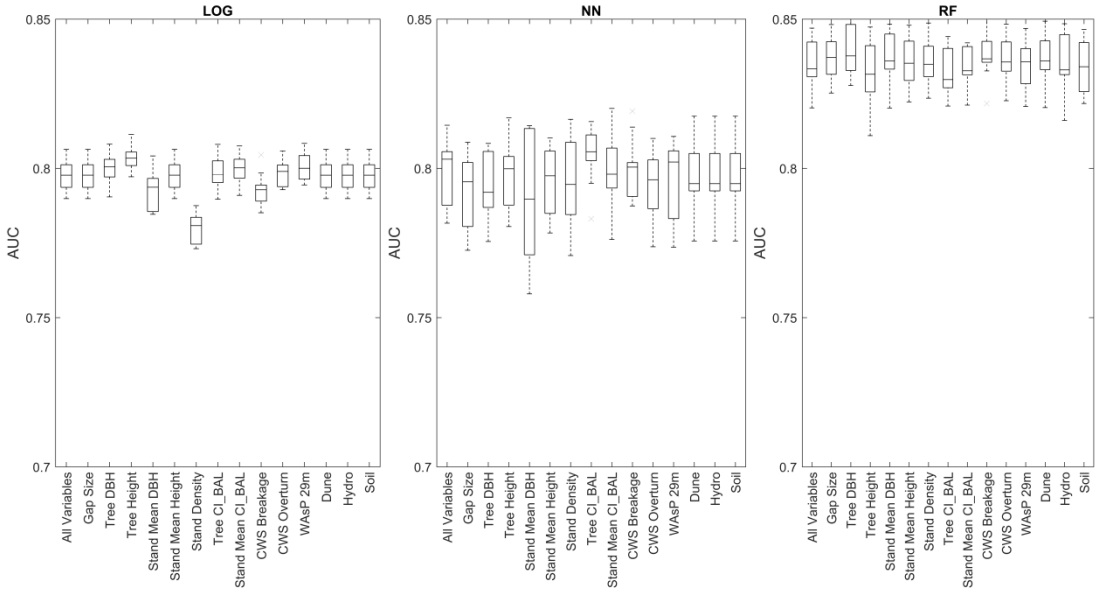
19

20 Fig. A 3: Accuracy and AUC for the LOG, NN and RF model predictions using the GALES predicted CWSs at
 21 29 m against the NFI damage data

22



23



24

Fig. A 4: Test of impact of leaving out each parameter in the models on the overall model accuracy and ability

25

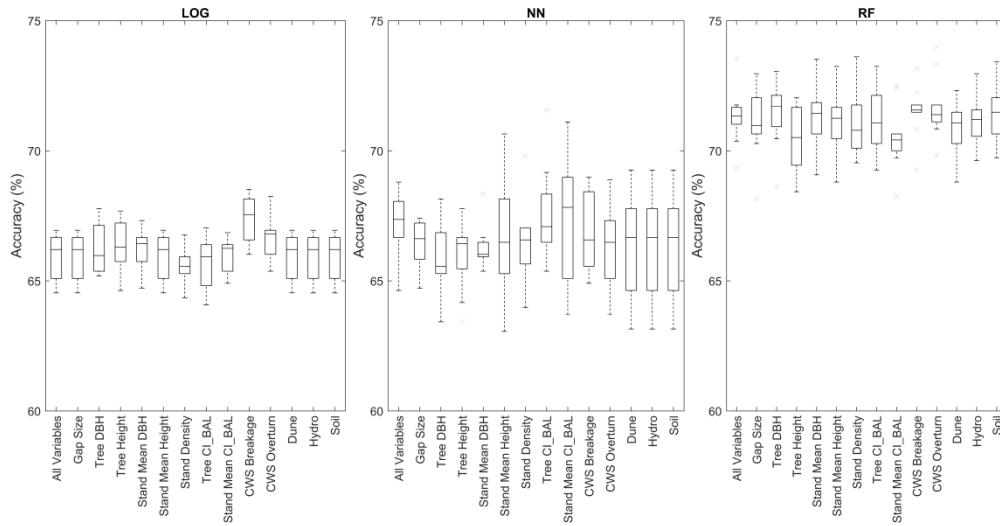
to discriminate between damage and no damage (AUC) for the Nezer Forest using CWS and WASP wind speed

26

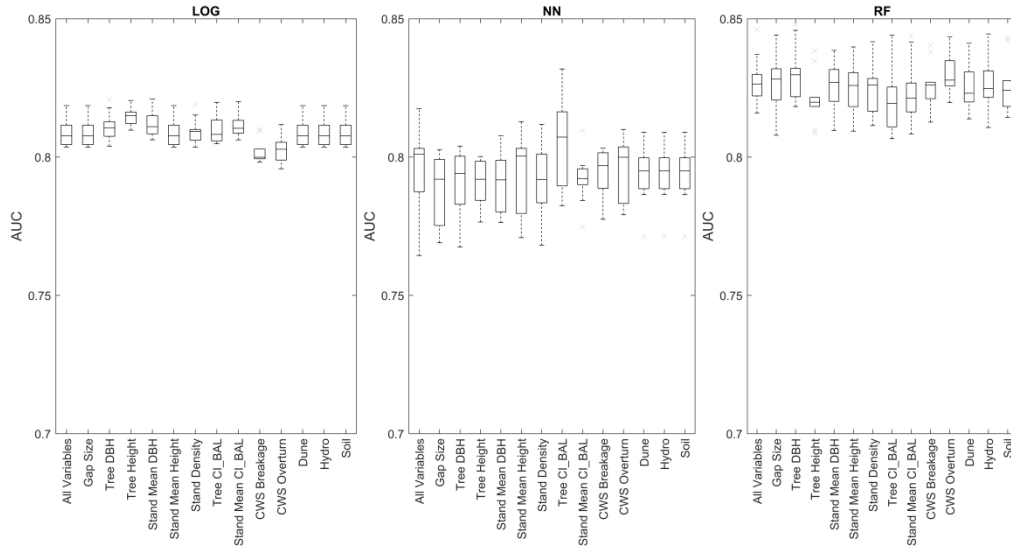
at 29 m.

27

28

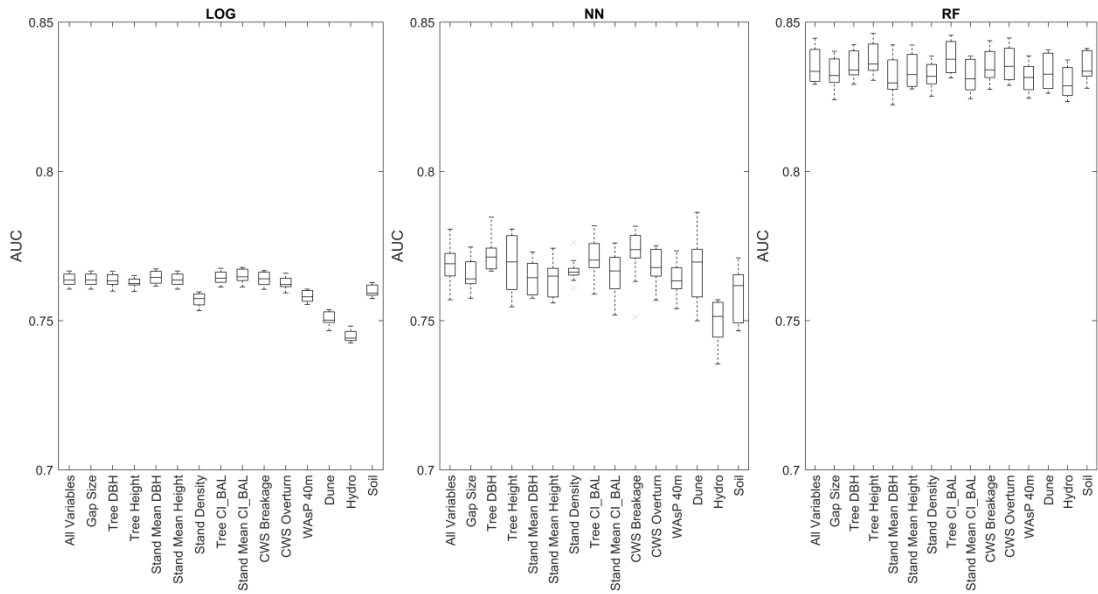
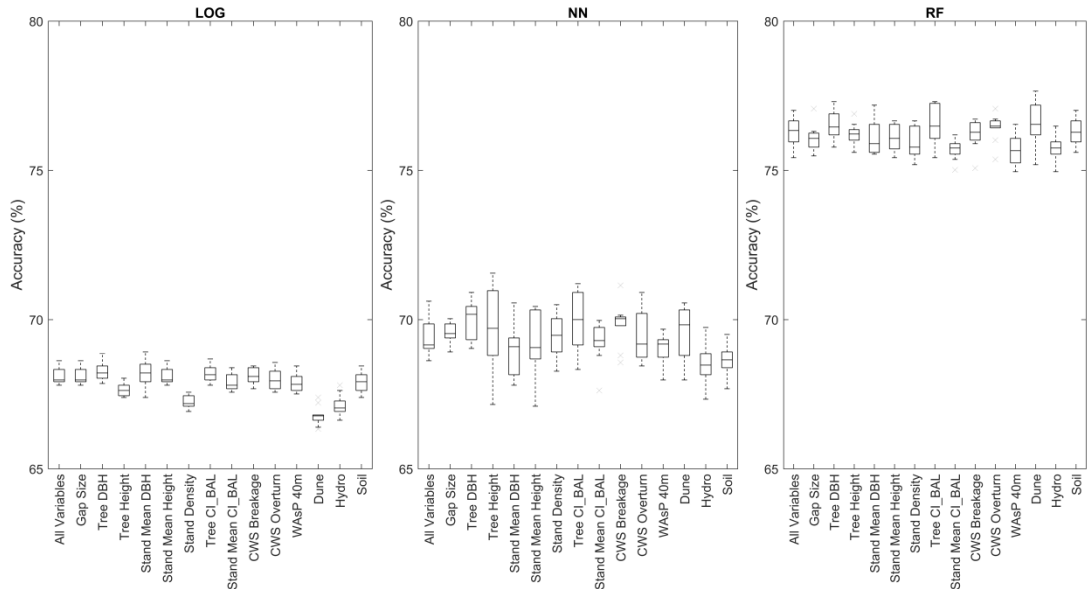


29



30 Fig. A 5: Test of impact of leaving out each parameter in the models on the overall model accuracy and ability
31 to discriminate between damage and no damage (AUC) for the Nezer Forest using CWS at $d+10$ m.

32

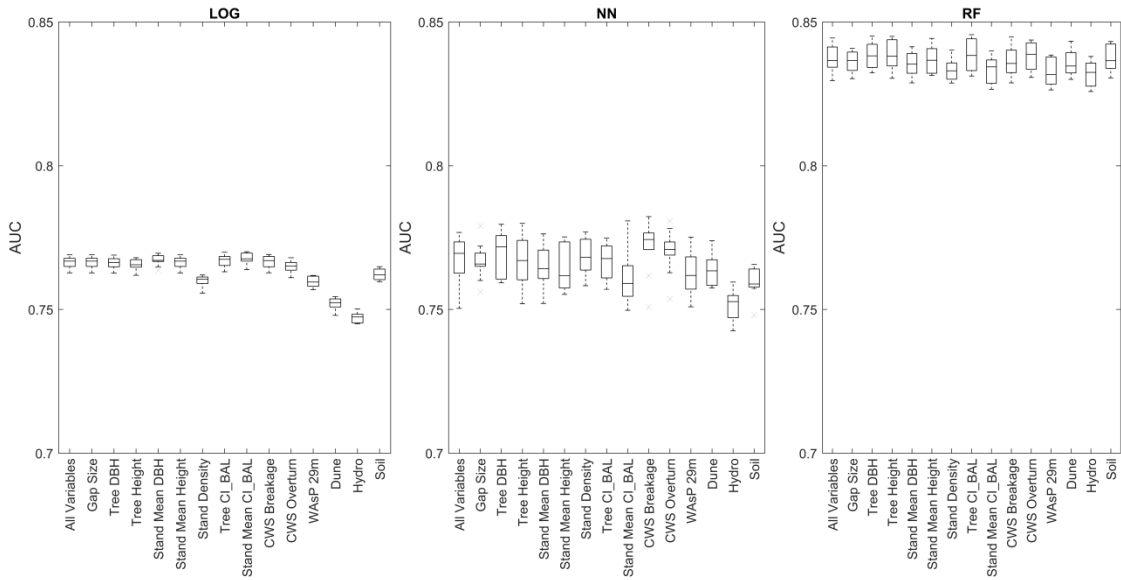
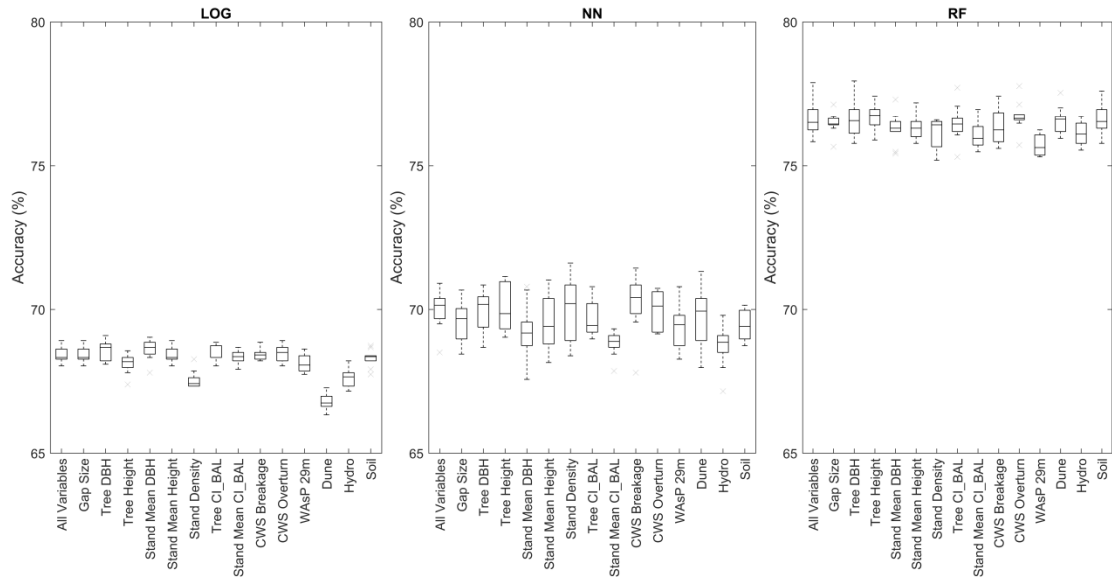


33

34

35 Fig. A 6: Test of impact of leaving out each parameter in the models on the overall model accuracy and ability
 36 to discriminate between damage and no damage (AUC) for the NFI data using CWS and WASP wind speed at
 37 40 m. Note change of scale from Fig. A 4 and Fig. A 5 for Accuracy.

38

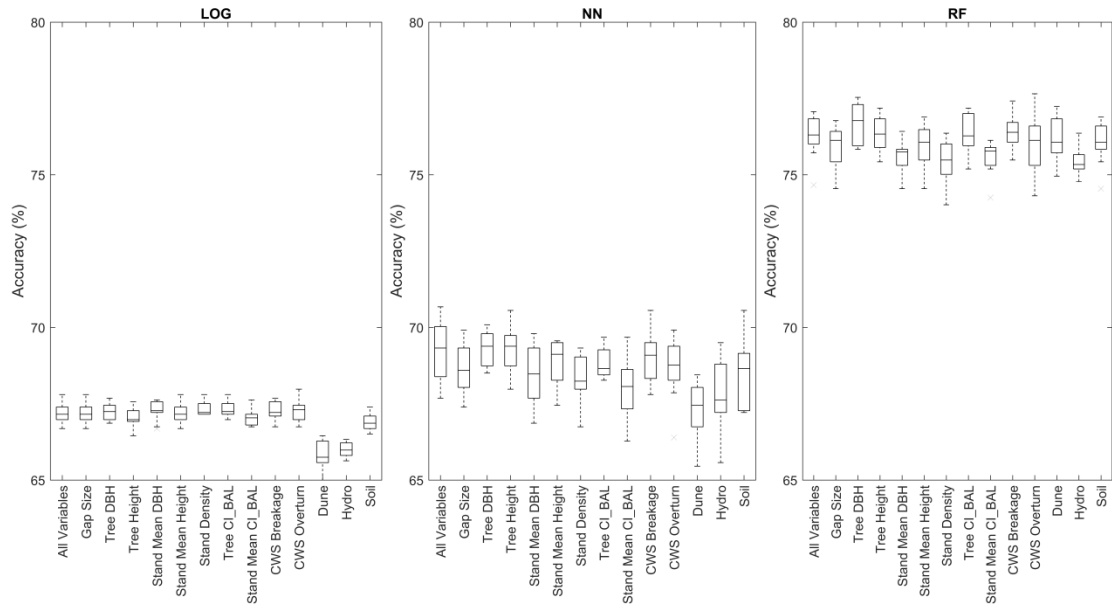


39

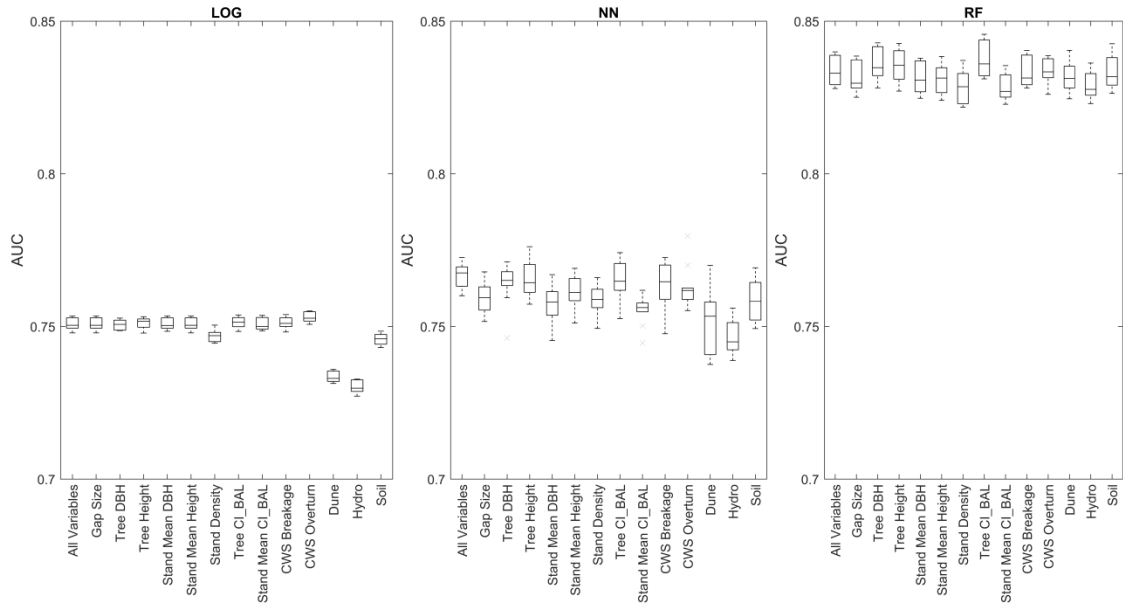
40

41 Fig. A.7: Test of impact of leaving out each parameter in the models on the overall model accuracy and ability
 42 to discriminate between damage and no damage (AUC) for the NFI data using CWS and WASP wind speed at
 43 29 m.

44



45



46

47 Fig. A.8: Test of impact of leaving out each parameter in the models on the overall model accuracy and ability
 48 to discriminate between damage and no damage (AUC) for the NFI data using CWS at $d+10$ m.

49

50 Table A 1: Results of comparison of predictions from trained LIN/NN/RF models and GALES for Nezer and
 51 NFI data at $d+10$ m. Numbers are correlation coefficient between trained model results and GALES predictions
 52 and root-mean square (RMS) error is given in brackets in ms^{-1} .

<i>Training Set</i>	<i>Test Set</i>	<i>Output</i>	<i>LIN</i>	<i>NN</i>	<i>RF</i>
GALES $d+10$ m predictions from artificial data	Nezer	CWS for breakage	0.9668 (3.5072)	0.9738 (6.8321)	0.9616 (5.0649)
GALES $d+10$ m predictions from artificial data	Nezer	CWS for overturning	0.9760 (3.2098)	0.9877 (2.8620)	0.9773 (3.1491)
GALES $d+10$ m predictions from artificial data	NFI	CWS for breakage	0.9362 (3.1918)	0.9495 (4.2107)	0.9493 (3.0381)
GALES $d+10$ m predictions from artificial data	NFI	CWS for overturning	0.9562 (2.0722)	0.9777 (1.7025)	0.9744 (1.7226)

53

54 Table A 2: Mean accuracy of different models with each model variable removed in turn. Standard deviation is given in brackets. * indicates value significantly different
 55 ($p < 0.05$) from the value with *All Variables*. The superscript letters against the values in the All column (a, b, or c) indicate whether there are significant differences between
 56 the models for that particular height of CWS calculation at the $p=0.5$ level.

Data Set	Model	CWS Height	All Variables	Average CI_BAL	CI_BAL	Tree DBH	Stand Density	Dune	Gap Size	Hydro	Stand DBH	Soil	Stand Height	Tree Height	CWS Break	CWS Overturn	WAsP Wind Speed
Nezer	LOG	d+10 m	65.972 ^a (0.839)	65.944 (0.667)	65.713 (0.984)	66.25 (0.915)	65.565 (0.681)	65.972 (0.839)	65.972 (0.839)	65.972 (0.839)	66.148 (0.838)	65.972 (0.839)	65.972 (0.839)	66.352 (0.97)	67.361* (0.863)	66.648 (0.913)	
	NN		67.176 ^a (1.346)	67.259 (2.433)	67.509 (1.854)	65.824 (1.339)	66.528 (1.504)	66.509 (92.003)	66.407 (0.98)	66.509 (2.003)	66.269 (0.822)	66.509 (2.003)	66.741 (2.223)	66.019 (1.346)	66.778 (1.464)	66.417 (1.708)	
	RF		71.306 ^b (1.066)	70.519 (1.238)	71.167 (1.225)	71.426 (1.243)	71.000 (1.178)	70.917 (0.991)	71.046 (1.313)	71.093 (0.939)	71.231 (1.201)	71.407 (1.075)	71.167 (1.273)	70.454 (1.195)	71.509 (0.99)	71.657 (1.197)	
NFI	LOG	d+10 m	67.202 ^a (0.309)	67.056 (0.270)	67.308 (0.248)	67.226 (0.287)	67.349 (0.246)	65.801* (0.518)	67.202 (0.309)	65.982* (0.233)	67.261 (0.327)	66.897 (0.270)	67.202 (0.309)	67.050 (0.303)	67.267 (0.307)	67.284 (0.382)	
	NN		69.267 ^b (0.996)	67.971 (1.067)	68.868 (0.496)	69.261 (0.562)	68.305 (0.779)	67.290* (0.995)	68.657 (0.864)	67.713* (1.172)	68.481 (0.985)	68.540 (1.064)	68.880 (0.716)	69.273 (0.814)	69.021 (0.834)	68.639 (0.999)	
	RF		76.240 ^c (0.693)	75.572 (0.559)	76.364 (0.664)	76.663 (0.680)	75.367 (0.763)	76.117 (0.773)	75.900 (0.664)	75.384 (0.452)	75.613 (0.510)	76.059 (0.700)	75.930 (0.683)	76.293 (0.622)	76.375 (0.567)	76.006 (0.950)	
	LOG	29 m	68.405 ^a (0.270)	68.364 (0.232)	68.428 (0.277)	68.569 (0.330)	67.560* (0.303)	66.798* (0.285)	68.405 (0.270)	67.613* (0.327)	68.604 (0.368)	68.311 (0.303)	68.405 (0.270)	68.117 (0.340)	68.434 (0.193)	68.469 (0.275)	68.129 (0.306)
	NN		69.988 ^b (0.673)	68.815 (0.435)	69.672 (0.623)	69.947 (0.726)	70.041 (1.064)	69.760 (0.999)	69.601 (0.654)	68.698* (0.722)	69.273 (0.962)	69.455 (0.521)	69.537 (0.965)	70.065 (0.809)	70.205 (1.015)	69.994 (0.643)	69.372 (0.729)
	RF		76.604 ^c (0.619)	76.065 (0.507)	76.475 (0.636)	76.669 (0.660)	76.158 (0.505)	76.587 (0.462)	76.481 (0.370)	76.123 (0.426)	76.299 (0.550)	76.622 (0.528)	76.364 (0.456)	76.663 (0.496)	76.352 (0.610)	76.710 (0.512)	75.695* (0.354)

59 Table A 3: Mean AUC of different models with each model parameter removed in turn. Standard deviation is given in brackets. * indicates value significantly different
 60 ($p < 0.05$) from the value with *All Variables*. The superscript letters against the values in the All column (a, b, or c) indicate whether there are significant differences between
 61 the models for that particular height of CWS calculation at the $p=0.5$ level.

Data Set	Model	CWS Height	All Variables	Average CI_BAL	CI_BAL	Tree DBH	Stand Density	Dune	Gap Size	Hydro	Stand DBH	Soil	Stand Height	Tree Height	CWS Break	CWS Overturn	WAsP Wind Speed	
Nezer	LOG	d+10 m	0.809 ^a (0.005)	0.812 (0.004)	0.81 (0.005)	0.811 (0.005)	0.809 (0.005)	0.809 (0.005)	0.809 (0.005)	0.809 (0.005)	0.812 (0.005)	0.809 (0.005)	0.809 (0.005)	0.815 (0.003)	0.802 (0.004)	0.803 (0.005)		
	NN		0.796 ^b (0.015)	0.792 (0.009)	0.805 (0.016)	0.791 (0.012)	0.791 (0.014)	0.794 (0.01)	0.789 (0.012)	0.794 (0.01)	0.791 (0.011)	0.794 (0.01)	0.794 (0.01)	0.795 (0.014)	0.791 (0.008)	0.793 (0.009)	0.795 (0.011)	
	RF		0.827 ^c (0.009)	0.823 (0.011)	0.82 (0.012)	0.83 (0.01)	0.825 (0.01)	0.825 (0.009)	0.827 (0.01)	0.826 (0.01)	0.826 (0.01)	0.826 (0.009)	0.826 (0.01)	0.826 (0.01)	0.821 (0.009)	0.826 (0.009)	0.83 (0.008)	
NFI	LOG	d+10 m	0.751 ^a (0.002)	0.751 (0.002)	0.751 (0.002)	0.751 (0.002)	0.747* (0.002)	0.733* (0.002)	0.751 (0.002)	0.730* (0.002)	0.751 (0.002)	0.746* (0.002)	0.751 (0.002)	0.751 (0.002)	0.751 (0.002)	0.753 (0.002)		
	NN		0.767 ^b (0.004)	0.755* (0.005)	0.765 (0.006)	0.764 (0.007)	0.759 (0.005)	0.752* (0.011)	0.760 (0.005)	0.747* (0.006)	0.757 (0.007)	0.759 (0.006)	0.761 (0.006)	0.765 (0.006)	0.764 (0.008)	0.763 (0.007)		
	RF		0.834 ^c (0.005)	0.828 (0.004)	0.838 (0.006)	0.836 (0.005)	0.828 (0.005)	0.832 (0.005)	0.831 (0.005)	0.829 (0.004)	0.831 (0.005)	0.833 (0.006)	0.831 (0.005)	0.836 (0.006)	0.834 (0.005)	0.833 (0.005)		
	LOG	29 m	0.766 ^a (0.002)	0.767 (0.002)	0.767 (0.002)	0.766 (0.002)	0.760* (0.002)	0.752* (0.002)	0.766 (0.002)	0.747* (0.002)	0.767 (0.002)	0.762* (0.002)	0.766 (0.002)	0.766 (0.002)	0.767 (0.002)	0.765 (0.002)	0.760* (0.002)	
	NN		0.768 ^a (0.008)	0.761 (0.009)	0.766 (0.007)	0.769 (0.008)	0.768 (0.007)	0.764 (0.005)	0.767 (0.006)	0.752* (0.005)	0.765 (0.007)	0.760 (0.005)	0.764 (0.008)	0.766 (0.009)	0.772 (0.009)	0.770 (0.008)	0.763 (0.008)	
	RF		0.837 ^b (0.005)	0.833 (0.005)	0.839 (0.006)	0.838 (0.005)	0.834 (0.004)	0.836 (0.004)	0.836 (0.004)	0.832 (0.004)	0.836 (0.004)	0.837 (0.005)	0.837 (0.005)	0.837 (0.005)	0.839 (0.005)	0.836 (0.005)	0.838 (0.005)	0.832 (0.005)

64 Table A 4: Accuracy and AUC values for the models when tested on other data set (Nezer models tested on NFI data and NFI models tested on Nezer data). Standard
 65 deviations are given in parentheses. Mean value when models were tested on the data sets from which they were developed on second line in square brackets (from Table 5
 66 and 6).

<i>CWS Height</i>	<i>Model Source Area</i>	<i>Model Test Area</i>	<i>LOG</i>		<i>NN</i>		<i>RF</i>	
			<i>Accuracy (%)</i>	<i>AUC</i>	<i>Accuracy (%)</i>	<i>AUC</i>	<i>Accuracy (%)</i>	<i>AUC</i>
d+10m	Nezer	NFI	53.443 (1.208) [65.972]	0.563 (0.013) [0.809]	50.358 (3.857) [67.176]	0.556 (0.040) [0.796]	54.411 (1.717) [71.306]	0.521 (0.019) [0.827]
29m	Nezer	NFI	52.657 (1.098) [66.954]	0.549 (0.011) [0.798]	53.836 (2.828) [68.741]	0.531 (0.531) [0.799]	52.440 (1.735) [72.528]	0.578 (0.026) [0.834]
d+10m	NFI	Nezer	69.981 (1.673) [67.202]	0.766 (0.005) [0.751]	59.676 (7.145) [69.267]	0.741 (0.054) [0.767]	73.778 (1.794) [76.240]	0.735 (0.022) [0.834]
29m	NFI	Nezer	73.102 (1.770) [68.405]	0.756 (0.008) [0.766]	60.787 (10.062) [69.988]	0.724 (0.032) [0.768]	75.537 (1.223) [76.604]	0.713 (0.026) [0.837]

67