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Comparison and validation of three versions of a forest wind risk model

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This paper is dedicated to the memory of Mike Raupach whose work on aerodynamic drag over rough surfaces forms the scientific basis of our modelling, and who will continue to inspire future generations.

Keywords:
Risk modelling
Decision support system
Wind damage
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ABSTRACT

Predicting the probability of wind damage in both natural and managed forests is important for understanding forest ecosystem functioning, the environmental impact of storms and for forest risk management. We undertook a thorough validation of three versions of the hybrid-mechanistic wind risk model, ForestGALES, and a statistical logistic regression model, against observed damage in a Scottish upland conifer forest following a major storm. Statistical analysis demonstrated that increasing tree height and local wind speed during the storm were the main factors associated with increased damage levels. All models provided acceptable discrimination between damaged and undamaged forest stands but there were trade-offs between the accuracy of the mechanistic models and model bias. The two versions of the mechanistic model with the lowest bias gave very comparable overall results at the forest scale and could form part of a decision support system for managing forest wind damage risk.

Software availability

Name of software: ForestGALES Developers: Forest Research and INRA Contact address: Forest Research, Northern Research Station, Roslin, Midlothian EH25 9SY, United Kingdom Email: forestgales.support@forestry.gsi.gov.uk Availability and Online Documentation: The software along with supporting material is freely available. Go to http://www.forestresearch.gov.uk/forestgales to find out how to obtain the software or email forestgales.support@forestry.gsi.gov.uk Year first available: 2000 Hardware required: IBM compatible PC Software required: MS Windows Programming language: Borland Delphi 5.0®. Versions have also been written in Python, Fortran, R and Java. Contact the corresponding author (barry.gardiner@bordeaux.inra.fr) for further details. Program size: 10 MB. With all additional support files and manuals = 25 MB.

1. Introduction

Wind is a major disturbance agent in forests and a key part of the dynamics of many forest ecosystems, particularly temperate forests (Johnson and Miyanishi, 2007). Therefore to understand how forest ecosystems function, and to gain insight into the structure of forests, we need to understand the mechanisms and occurrence of wind damage. In addition, the high levels of damage that can occur in storms have important economic, environmental

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Symbols and abbreviations

$canopybreadth$	Maximum width of canopy (m)
$canopydepth$	Length of the live crown (m)
C	Drag coefficient scale parameter
C_D	Drag coefficient (percentage reduction in canopy area due to streamlining)
C_{reg}	Regression between stem weight (SW) and resistance to overturning (Nm kg^{-1})
CWS	Critical wind speed for damage (m s^{-1})
d	Zero-plane displacement (m)
d_0	Stem diameter at base of tree (m)
dbh	Stem diameter at breast height (1.3 m) (m)
D	Average spacing between trees (m)
$DAMS$	Windiness score from Quine and White (1993)
f_{CW}	Dimensionless factor to account for additional turning moment due to crown and stem weight
f_{knot}	Dimensionless factor to account for reduction in clear wood *MOR* due to knots
G	Dimensionless factor to account for gustiness of wind
h	Tree height (m)
k	von Karman constant = 0.4
M_{appl_max}	Maximum turning moment due to wind loading only and not including additional moment due to overhanging crown and stem (Nm)
MOR	Modulus of rupture on wood for species of interest (Pa)
n	Parameter controlling reduction in drag coefficient with wind speed
ρ	Density of air (kg m^{-3})
SCDB	Forestry Commission sub-compartment database
$Spacing\_Ratio$	Ratio of average tree spacing after and before a thinning
SW	Stem (bole) weight (kg)
T_C	Turning moment coefficient from Hale et al. (2012) (kg)
TMC_Ratio	Ratio of turning moment coefficient after and before thinning
$u(d+10)$	Wind speed at 10 m above the zero plane displacement height (m s^{-1})
$u(h)$	Wind speed at tree height (m s^{-1})
u_*	Friction velocity (m s^{-1})
$Weibull\_A$	Weibull scale parameter (m s^{-1})
$Weibull\_k$	Weibull shape parameter (dimensionless)
$Wind\_DAMS$	Wind speed calculated from DAMS score (m s^{-1})
$Wind\_WAsP$	Wind speed calculated from WAsP airflow model (m s^{-1})
WS	Wind speed at meteorological station (m s^{-1})
x	Distance from forest edge (m)
YC	Yield class (m^3 ha^{-1} yr^{-1})
z_0	Aerodynamic roughness (m)

and social consequences, particularly for managed forests (Gardiner et al., 2010). Understanding the process of wind interactions with forests, the impact of forest damage, the potential for preventive responses, and the prospects for the future are therefore important for people engaged in the forest-based economy, for forest ecologists, for regional planners, and for anyone concerned with the continued sustainability of forests and the forestry sector.

Wind is the major disturbance agent for European forests and is responsible for more than 50% of all damage by volume (Schelhaas et al., 2003; Gardiner et al., 2010). The cost of such damage can be very high in economic terms (e.g. € 6 billion in France from storms Lothar and Martin in 1999, and € 2.4 billion in Sweden after storm Gudrun in 2005), as well as having a huge impact on local societies and forest ecosystems (see Blennow et al., 2014; Gardiner et al., 2013). Worryingly, there is evidence that damage levels have been increasing over the past century (Schelhaas et al., 2003), and are likely to continue to increase in the future (Gardiner et al., 2010; Schelhaas et al., 2010). Part of this increase appears to be due to a changing climate, with wetter and warmer winters leading to longer periods of saturated soils, and to longer periods with unfrozen soils in Fennoscandia (Usbeck et al., 2010). However, the increase also appears to be influenced by forest management practice (Seidl et al., 2011), such as the increase in growing stock of European forests because of longer rotations, and the increase in delayed thinning due to the lack of profitable markets for small roundwood. Forest management is known to have a significant influence on forest vulnerability to wind damage (e.g. Albrecht et al., 2012; Gardiner et al., 2005; Hale et al., 2004; Mason, 2002; Mason and Quine, 1995; Valinger and Fridman, 2011). Understanding the impact of forest management is therefore important for planning damage mitigation strategies. A key component of any risk management and risk mitigation strategy is to have a method for predicting the level of risk, so that the implications of different options can properly be assessed (Gardiner and Quine, 2000; Gardiner and Welton, 2013).

A number of methods of assessing wind risk have been developed. These began with the Windthrow Hazard Classification (WHC) (Miller, 1985), which is a scoring system developed in Great Britain that uses measures of local topographic shelter and rooting depth to predict the height at which wind damage would be expected to begin in thinned and unthinned stands. The relative weighting of the shelter and rooting factors was based on expert judgement and observations of damage. However, the WHC is essentially a site scoring system and does not allow for differences in silviculture or species choice. It has never been fully validated, but is thought to be pessimistic, predicting damage to start on average at too low a tree height (Quine, 1995).

Another approach is to develop empirical models based on inventories of past damage. These require large amounts of high quality data across a range of site conditions, and may only be usable in the area from which the inventory data were obtained, and for the types of storm on which the analyses were based. An example of such a model is “Lothar”, which is based on a detailed inventory of around 1300 plots following storm damage in the Black Forest in 1990 and 1999 (Schmidt et al., 2010). Previous statistical analysis of storm damage (e.g. Albrecht et al., 2012; Colin et al., 2009; Schmidt et al., 2010; Valinger and Fridman, 2011) has identified a number of factors that appear to be associated with storm damage to stands, although they are not always the same from analysis to analysis. Of all the factors that appear to have an influence on wind risk, tree height is the most important and consistent factor from all analyses. In addition recent thinning, the creation of new edges, the presence of waterlogging, and soils with restricted rooting or acidic soils have been shown to be factors predisposing stands to damage. The relative stability of different species has been the subject of much debate and contradictory evidence, but overall it appears that spruces are amongst the most vulnerable of conifers (Colin et al., 2009; Hanewinkel et al., 2008, 2013). Within stands, the trees with the highest taper appear to be the most wind-firm, through being at least risk from stem breakage (Gardiner et al., 1997; Hanewinkel et al., 2013). Slopes and valleys exposed to the prevailing wind are particularly susceptible to wind damage (Schmidt et al., 2010), which is in accordance with the analysis of the importance of funnelling in the DAMS scoring system of Quine and White (1993). Interestingly, increasing elevation has been shown to have a correlation with decreasing levels of risk (Albrecht et al., 2013; Lanquaye-Opoku and Mitchell, 2005) suggesting an acclimation to the wind at higher elevations and wind exposure.

The third approach is the use of hybrid mechanistic-empirical models such as HWIND (Peltola et al., 1999), FOREOLE (Ancelin et al., 2004) and GALES (Gardiner et al., 2000), which as much as possible use mechanical engineering calculations to determine the wind loading on trees and the speeds causing uprooting or breakage (Gardiner et al., 2008). They are called hybrid models because some elements of the calculation cannot currently be calculated using purely mechanistic approaches and require empirical relationships. For example, resistance to uprooting uses empirical correlations with tree size, soil type and rooting depth based on tree winching studies (Nicoll et al., 2006). These hybrid mechanistic-empirical models use characteristics of the forest stand and site to calculate the critical wind speed (CWS) that will cause damage to the trees, combined with knowledge of the local wind climate (using wind climate data or airflow models) to estimate the likelihood of the CWS being exceeded. ForestGALES (Dunham et al., 2000; Gardiner et al., 2004) is an example of such a combination, using GALES to calculate CWS and the DAMS windiness scoring system (Quine and White, 1993) to predict the probability of damage through the life of a forest stand, based on tree dimensions and stand and site characteristics. It uses the idea of momentum stress partitioning (Raupach, 1994) between trees to calculate the wind loading on individual trees in the forest, and a gust factor to convert from mean to extreme wind loading. We refer to this method as the “roughness” method. ForestGALES is in use in Great Britain, where it has replaced the WHC as the recommended decision support system for managing wind risk in commercial forestry (Forestry Commission, 2010). It has also been adapted for use in Brazil, Canada, Denmark, France, Japan and New Zealand (Byrne, 2005; Cucchi et al., 2005; Kamimura et al., 2008; Mikklesen, 2007; Moore and Somerville, 1998; Ruel et al., 2000).

However, a model is only as good as the data against which it has been validated, and validation of forest wind risk models is inherently difficult because of the relative infrequency of storms that cause severe damage. Furthermore in the event of a damaging storm, a model cannot be validated without having a comprehensive survey of the damage, and knowing the characteristics of the forest at the time of the storm, together with the wind speeds over the forest during the storm; these are seldom all available. To date there have been only a few attempts to conduct systematic validation exercises on hybrid mechanistic-empirical wind risk models. Byrne and Mitchell (2013) tested a modified version of ForestGALES adapted for conditions in British Columbia, Canada; the comparisons at a single experimental location indicated that the model gave reasonable predictions against observed damage, although there were some differences between species. Seidl et al. (2014) developed a wind risk model from the experimental measurements of Hale et al. (2012), which is very similar to the third version of ForestGALES discussed below, and obtained good comparison with observed patterns and levels of damage in Southern Sweden. However, an initial partial validation of ForestGALES in Great Britain (Gardiner et al., 2008; Suárez et al., 2002), together with the experience of wind damage of British foresters, has indicated that the model is over-pessimistic in its predictions of damage (i.e. predicts more damage than is observed) at least under British conditions. This is thought to be due to exaggerated values for the gust factor in the model (Gardiner et al., 2008). This has implications for forest managers, as they may fell a crop on the basis of its predicted wind risk, when in fact it could have grown for longer with a greater economic return. At the same time, Hale et al. (2012) have provided a new approach to predicting CWS from a direct prediction of the maximum turning moment on a tree based on the tree characteristics, without the need for a gust factor. We hereafter refer to this approach as the “turning moment coefficient” or TMC method. This paper presents a comparison of the two approaches to calculating wind risk to forests (“roughness” and “turning moment coefficient” methods) within the hybrid mechanistic-empirical wind risk model ForestGALES, and is the first comprehensive assessment of these models for forests in the Great Britain.

On 3rd January 2012 a deep Atlantic depression caused strong winds across much of the UK. Central Scotland was the worst affected area with recorded gusts well over 36 m s^{-1}, causing substantial wind damage in several forest districts. Cowal and Trossachs Forest District, in the west of central Scotland, reported over 150 ha of wind damage resulting from the storm, with the loss of approximately 180,000 tonnes of timber (over 150,000 m^3). The damage was monitored by aerial helicopter flights across the whole district just after the storm, and together with the fact that there was information on the forest prior to the storm within the Great Britain Forestry Commission database, we decided that this storm would be an excellent opportunity for assessing the performance of different versions of the ForestGALES model. The information was also sufficiently detailed to allow statistical analysis of which factors were associated with wind damage, and therefore to compare purely empirical and hybrid mechanistic-empirical approaches.

The specific aims of this study were:

i. to conduct an initial assessment of the performance of three versions of ForestGALES: the original methodology using the “roughness” method requiring a gust factor, a version with a reduced gust factor, and the new “turning moment coefficient” method that avoids the use of a gust factor,
ii. to assess what factors were most important in determining wind damage in a typical managed coniferous forest in Great Britain by developing a logistic regression model,
iii. to compare the performance of ForestGALES and the logistic regression model against observed damage,
iv. to assess the implications of using different modelling options and approaches for the management of wind risk in British forests.

2. Method

2.1. Study area

Cowal and Trossachs Forest District (55.6°N, 4.8°W), in west central Scotland, has varied topography, being relatively flat in the east, mountainous to the north, and with extensive lochs and coastal areas. The climate is cool and wet in the west, and warmer and drier in the east; rainfall ranges from 1000 to 2500 mm yr^{-1}. Many of the valleys are sheltered, but on the peaks wind speeds of over 40 m s^{-1} occur with a 10–15 year return cycle (Anon., 2009). Soils are a mixture of brown earths, podzols, ironpans, gleys and peats, commonly occurring as complexes within an individual forest stand. The forest is used for commercial timber production, but there is also high recreation and amenity value, with a national park lying entirely within the district.

The total forest district area was 69,245 ha in 2012, of which 37,679 ha (54%) was forested. Most of the forest area was plantation (about 88%) with 12% native woodland. The most abundant species was Sitka spruce (*Picea sitchensis* (Bong.) Carr.), which covered 64% of the forest area. Other common species were larches (*Larix* spp.) (6% of forest area), Norway spruce (*Picea abies* (L.) Karst) and birch (*Betula* spp.) (each 4%). There were peaks in planting during the 1960s and the 1980s, but planting has continued up to the present, and there are also stands up to 200 years old. Traditionally forest management has been clearfell and replant. However in the past ten to fifteen years alternative management approaches have been implemented, in keeping with national forestry policy (Anon., 2000, 2006). For example, continuous cover forestry systems meet the requirements for visual amenity (Anon., 2009), and have been introduced in a number of sheltered valleys.

The unit of forest management within the Forestry Commission in Great Britain is a sub-compartment (SC), with information centrally held in the Sub-compartment Database (SCDB) (Forestry Commission, 2008), which is kept up-to-date as SCs are planted and felled (or, e.g., wind blown). The SCDB for Cowal and Trossachs provided the input data for ForestGALES in this study, with a SC as the unit of input for each individual ForestGALES calculation. Of the 12,238 SCs assessed, 6996 SCs were productive forest with species for which ForestGALES has been parameterised (Table 1). This subset of the district was prepared as input to ForestGALES, and is referred to hereafter as the validation data set. These SCs ranged from 0.1 to 68 ha in size, with about 60% being between 1 and 10 ha.

2.2. *Observed damage*

In the days following the storm in January 2012 a helicopter survey was done to assess the wind damage across the forest district. A map was produced in GIS format, enabling a shape file of damage to be overlain on a map of the SCs. Damage occurred in patches mainly across the south of the district. Any SC that was overlain in whole or in part by a damage shape was noted as having damage, giving a total of 134 SCs identified as damaged (approximately 2% from the 6996 in the validation data set). Identifying part-damaged SCs as fully damaged exaggerates the actual damage to an extent, but it will be counteracted in part by the fact that the helicopter survey will inevitably have missed some smaller areas of damage. Furthermore, in this paper we are primarily concerned with the number of SCs damaged, because ForestGALES only predicts whether damage is expected in a stand or not and currently gives no estimation of the level of damage in a SC. A similar approach was taken by Valinger and Fridman (2011) to estimate the area affected by storm Gudrun, based on assessment of inventory plots. An airborne survey of damage in the Black Forest following storm Lothar detected individual areas of damage larger than 1.5 ha, but a ground survey suggested that the total area damaged was actually twice that detected by the airborne survey (Schmoeckel and Kottmeier, 2008). Subsequent analysis of airborne LiDAR measurements in Aberfoyle Forest (part of the forest district) also suggested that the helicopter survey underestimated the total area of damage (Suárez 2014, pers comm). Therefore, comparing predictions of the number of damaged SCs against a helicopter survey of the number of SCs containing damage is more appropriate than attempting to compare the total area of damage.

In Cowal and Trossachs Forest District, most species were damaged approximately in proportion to their occurrence in the district (see Table 2); however, Scots pine and Douglas-fir were notably under-represented, and Sitka spruce was slightly over-represented. There was no damage to Corsican pine or noble fir, but there were few SCs of these species. Almost two-thirds of the damaged SCs were Sitka spruce, so this dominated the age class distribution of damaged stands with the majority of Sitka spruce stands being less than 60 years old. Stands in the 31–40 and 41–50 year-old age classes were over-represented proportional to their occurrence, and those in the 61–70 year-old age class were under-represented (Table 3). Norway spruce and Scots pine were both dominated by stands aged 51–90 years old (with the exception of some recent planting of Scots pine). Norway spruce experienced damage to these older stands, but there was almost no recorded damage to Scots pine.

Table 1
Species parameterised in ForestGALES.

Common name	Latin name	Abbreviation
Sitka spruce	*Picea sitchensis* (Bong.) Carr.	SS
Norway spruce	*Picea abies* (L.) Karst	NS
Scots pine	*Pinus sylvestris* L.	SP
Lodgepole pine	*Pinus contorta* Dougl. ex Loud.	LP
Corsican pine	*Pinus nigra* subsp. *laricio* (Poir.) Maire	CP
European larch	*Larix decidua* Mill.	EL
Japanese larch	*Larix kaempferi* (Lamb.) Carr.	JL
Hybrid larch	*Larix x eurolepis* Henry	HL
Douglas-fir	*Pseudotsuga menziesii* (Mirb.) Franco	DF
Grand fir	*Abies grandis* (Dougl.) Forbes	GF
Noble fir	*Abies procera* Rehder	NF
Western hemlock	*Tsuga heterophylla* (Raf.) Sarg.	WH

2.3. *Stand characteristics: model input data*

The current ("roughness") version of ForestGALES requires species, spacing, soil type, rooting depth, mean tree diameter at breast height (*dbh*, measured at 1.3 m above the ground), and mean tree height or top height (average height of 100 largest-*dbh* trees per hectare) as input. The TMC method (Hale et al., 2012) additionally requires spacing before last thinning, and time since thinning (see Section 2.5 for details). In the forest, a SC can contain more than one species, although within the SCDB the information on component species is not held spatially. For all SCs, the main component species was used as the only input to ForestGALES, in order to generate one row of input data for each SC. In the validation data set the main component species mostly comprised 60–100 % of the SC area, but in some cases it was as low as 20%. Tree height, diameter and spacing have not historically been recorded in the SCDB. Instead, we used the species, management model, initial spacing and yield class (maximum volume increment in m^3 ha^{-1} yr^{-1}) to identify the yield table associated with each SC, based on the yield models produced by Edwards and Christie (1981). ForestGALES locates the relevant yield table for each SC and, inferring age from planting year, interpolates within the yield table to extract the estimated *dbh*, mean height and current spacing. Spacing before thinning, and time since thinning, can also be calculated from these yield tables. Soil type data were available in the SCDB for approximately 60% of the SCs in the validation data set; these were allocated a rooting depth (shallow, medium or deep) based on knowledge of what would be typical for each soil type (Ray and Rayner, 2002). For the remaining SCs a default soil type, a gleyed soil with medium rooting depth, was selected as being very typical of the forest district. All SCs were assumed to have a windfirm upwind edge, i.e. assumed not to be adjacent to a recent clear-felling or road construction, which would make the stand particularly vulnerable. The yield class and elevation from the SCDB, and values of *dbh*, top height and spacing as derived by ForestGALES from the relevant yield tables, were also used to develop the logistic regression model (see Section 2.7) in order to ensure the analysis data sets were identical.

There are clearly limitations to this input data. For example, the derivation of *dbh*, tree height and spacing from a yield table will only give results that accurately represent the trees in the SC if the specified management model has been adhered to and the yield class is correct; this is probably the most significant source of error in this data set. For older stands, yield class would have been assessed based on measurements made early in the rotation; for restock sites an estimate is made based on site conditions and the previous crop. There is a rolling programme of surveys for validation of yield class, targeting pre-thinning conifer stands (aged 15–20 years) and the SCDB is regularly checked and updated in each Forest District from these surveys and aerial photography, with a new version provided across the Forestry Commission each year (Forestry Commission, 2012). Ground-based measurements in a sample of Sitka spruce plots in the eastern part of the study area showed generally good agreement (e.g. $r^2 = 0.74$ for yield class) with the corresponding information in the SCDB (Suárez, 2010; Suárez pers comm, 2014). However, there can be substantial variation across an individual SC that is not captured by the single value attributed to it in the SCDB.

Where soil type is provided in the SCDB, it is based on interpretation of a soil profile from a representative part of the SC. The accuracy of this varies due to differences in the experience of foresters, and due to variation of soils within a SC, particularly SCs that are very large. For a SC that did not experience damage throughout its whole area, the information available to us did not enable identification of which particular species was damaged and we had to assume damage occurred to the main species component. However, when considering these limitations it is important to remember that the fundamental aim of this study was to assess with what level of accuracy, and at what spatial scale, we can predict wind damage with the normally-available data for British foresters (e.g. stand forest management or inventory data).

2.4. *Wind speeds during storm*

To assess whether damage would be predicted by ForestGALES for each SC it is necessary to know the wind speed above each SC during the storm. There was no anemometer within the forested area of the district. The nearest wind measurements were from Bishopton (low-lying ground west of Glasgow, near the southern edge of the forest district) and Glen Ogle (a mountain station 60 km north-east of Bishopton, at the northern edge of the forest district). Hourly wind speed data were obtained for both of these stations covering the period of the storm on 3rd January 2012 (UK Met Office, 2002). Maximum average hourly wind speed during the storm was 32.5 m s^{-1} for Glen Ogle, and 21.1 m s^{-1} for Bishopton. This corresponded to a return period of 60 years and 380 years at Glen Ogle and Bishopton, respectively. Two methods were used to estimate the above-canopy wind speed across the forest district during the storm: (i) WAsP, a computational linearised fluid dynamics model and (ii) DAMS, a scoring system based on wind zone and topographic exposure.

Table 2
The total number of SCs, and the number of damaged SCs, for each species. A proportion higher than 1 indicates a species which had more damage than would be expected if damage had been spread equally across all species. Species codes are given in Table 1 and results of particular interest are marked in **bold**.

	CP	DF	EL	GF	HL	JL	LP	NF	NS	SP	SS	WH	Total
N SCs	8	165	123	23	336	562	353	60	668	594	4012	92	6996
N SCs damaged	0	1	2	0	7	11	4	0	12	2	94	1	134
Proportion	0.0	**0.3**	0.8	0.0	1.0	1.0	0.6	0.0	0.9	**0.2**	1.2	0.5	

Table 3
The total number of SCs, and the number of damaged SCs, for each age class. A proportion higher than 1 indicates an age class which had more damage than would be expected if damage had been spread equally across all age classes. Results of particular interest are marked in **bold**.

	1–10	11–20	21–30	31–40	41–50	51–60	61–70	71–80	81–160	Total
N SCs	721	715	1003	822	1136	1312	504	549	234	6996
N SCs damaged	0	2	12	39	53	9	12	7	0	134
Proportion	0.0	0.1	0.6	**2.5**	**2.4**	**0.4**	1.2	0.7	0.0	

2.4.1. WAsP

WAsP (Wind Atlas Analysis and Application Programme; Mortensen et al., 1993) is a computer package that can extrapolate a wind rose from one location to another, taking into account local roughness, obstacles and topography at both locations, and assuming that both locations are subject to essentially the same weather systems (same wind climate). The wind data used as input for WAsP were based on the measured wind speeds at Bishopton on 3rd January 2012, with wind speed predictions made 10 m above the zero-plane displacement height (d) at a horizontal resolution of 100 m over the whole of Cowal and Trossachs. The peak hourly wind speed of 21.1 m s^{-1} from a direction of 260° was recorded between 9:00–10:00 GMT but during the previous hour the mean hourly wind speed reached 19.0 m s^{-1} from a direction of 240°. WAsP runs were performed for each of these two periods and the higher of the two wind speeds was selected at each grid point (the change in wind direction during the storm meant that the peak hourly wind speed did not necessarily result in the higher modelled wind speed at all locations). These were output as 100 m grid cells in raster format with the point value at their centre. The raster data were read into ArcGIS and evaluated at SC scale, giving a single value for each SC that represented the average above-canopy wind speed based on the grid points lying within the SC. These values will be referred to as *Wind_WAsP* in the remainder of the paper.

The digital terrain data providing the elevations used in WAsP were obtained from the NASA ASTER Global Digital Elevation Model (Hirano et al., 2003). The data have a vertical accuracy of 17 m at the 95% confidence level, and a horizontal resolution on the order of 75 m. Aerodynamic roughness values (z_0) and zero-plane displacement (d) in WAsP were according to Table 4 with d being added to the NASA derived elevations. The values for the forested area were those calculated within ForestGALES for the SCs included in the validation data set and their derivation is discussed in more detail in the online supplement.

2.4.2. DAMS

A drawback of WAsP is that it was not designed for use over forested terrain and there is uncertainty of the best way to represent the aerodynamic roughness of forests (Crockford and Hui, 2007; Dellwik et al., 2006). In contrast, DAMS (Detailed Aspect Method of Scoring) is a measure of windiness based on the local wind zone, elevation, aspect and topographic exposure (Quine and White, 1993) and was designed to provide a measure of exposure for forests. The wind speed distribution at individual locations in Great Britain is well described by the Weibull distribution (Cook, 1985), with the Weibull shape parameter (*Weibull_k*) being relatively constant, and the scale parameter (*Weibull_A*) being related to the mean wind speed (WS_{mean}) through the expression:

$$WS_{mean} = Weibull\_A \cdot \Gamma(1 + 1/1.85) = Weibull\_A \cdot 0.888 \tag{1}$$

where Γ is the gamma function (see Troen and Petersen, 1989).

Table 4
Roughness length and zero-plane displacement used in WAsP according to land use.

Land use	Roughness length (m)	Zero-plane displacement (m)
Open water	0.0002	0.0
Open ground/agriculture	0.05	0.0
Forest[a]	1.45 (0.36–5.25)	11.83 (2.0–31.70)

[a] Mean values (limits in parentheses). See online supplement for derivation method for the forest values.

Weibull parameters are used within ForestGALES to calculate the annual exceedance probability of the CWS, using a constant value of *Weibull_k* = 1.85, and calculating *Weibull_A* from DAMS as shown below for forested and non-forested areas (Equations (2) and (3), respectively; Quine, 2000):

$$Weibull\_A = 0.4279 \cdot DAMS - 0.9626 \text{ (forested areas)} \tag{2}$$

$$Weibull\_A = 0.378 \cdot DAMS + 0.5867 \text{ (open ground)} \tag{3}$$

The DAMS data set associated with ForestGALES contains gridded values of DAMS at 50 m resolution. In this forest DAMS values ranged from 8 (sheltered: mean wind speed = 2.2 m s^{-1}) to 21 (very exposed: mean wind speed = 7.1 m s^{-1}) with a mean of 13, and the DAMS values at Bishopton and Glen Ogle are 11.5 and 18.0, respectively. By overlaying the SC outlines on the DAMS map, an average value of DAMS was found for each SC in the validation data set. Suárez et al. (1999) have already shown DAMS to be a good predictor of wind speeds in complex forested terrain and, assuming that the *Weibull_A* ratio between different locations during the storm is equivalent to the wind speed ratio from Equation (1), then DAMS can be used to estimate the above-canopy wind speed at each SC during the storm from Equation (4) (note the wind speed and DAMS from Bishopton were used, as this location lay closer to the path of the storm centre than Glen Ogle).

$$Wind\_DAMS_{SC} = \frac{0.4279 \cdot DAMS_{SC} - 0.9626}{0.378 \cdot DAMS_{Bishopton} + 0.5867} \cdot WS_{Bishopton} \tag{4}$$

where $Wind\_DAMS_{SC}$ is wind speed for a sub-compartment, $DAMS_{SC}$ is DAMS for a sub-compartment, $DAMS_{Bishopton}$ is DAMS at Bishopton, and $WS_{Bishopton}$ is the wind speed at Bishopton.[1] The wind speed is assumed to be at 10 m above the zero-plane displacement (d) of the forest (see discussion in Section 2.6).

There are spatial limitations with both of these methods of estimating the above-canopy wind speed for a SC. Some SCs are made up of two (or more) discrete blocks, which may have rather different exposure and wind speed. In these cases the average wind speed for the SC may not represent the wind speed that caused damage across only part of the SC.

2.5. ForestGALES

In this section we present the equations from ForestGALES used for calculating the CWS for overturning and breakage, including the new approach that is based on the work of Hale et al. (2012). A discussion of the background to the ForestGALES model and the modelling approach can be found in Gardiner et al. (2000, 2008). The basic mechanical engineering equations are presented in Quine and Gardiner (2007) and a full derivation is provided in the online supplement.

2.5.1. ForestGALES 2.3 [FG2.3]

The equations for ForestGALES 2.3, described below, are from the release version in use within Great Britain at the time of this study.

The CWS at canopy top for overturning and stem breakage ($u(h)_{crit\_over}$ and $u(h)_{crit\_break}$, respectively, in m s^{-1}) are given by:

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[1] As an illustration of the method the Bishopton wind speed, and DAMS from Bishopton and Glen Ogle, were used to estimate the wind speed at Glen Ogle. With $DAMS_{\text{Bishopton}}$ = 11.5 and $WS_{\text{Bishopton}}$ = 21.1 m s^{-1} (peak of storm), and $DAMS_{\text{GlenOgle}}$ = 18, the wind speed predicted at Glen Ogle was 31.6 m s^{-1}, which is close to the actual recorded value of 32.5 m s^{-1}.

$$u(h)_{crit\_over} = \frac{1}{kD}\left[\frac{C_{reg}\cdot SW}{\rho G d}\right]^{\frac{1}{2}}\left[\frac{1}{f_{CW}}\right]^{\frac{1}{2}}\ln\left(\frac{h-d}{z_0}\right) \tag{5}$$

$$u(h)_{crit\_break} = \frac{1}{kD}\left[\frac{\pi\cdot MOR\cdot dbh^3}{32\rho G(d-1.3)}\right]^{\frac{1}{2}}\left[\frac{f_{knot}}{f_{CW}}\right]^{\frac{1}{2}}\ln\left(\frac{h-d}{z_0}\right) \tag{6}$$

where h is the average tree height (m) and dbh (m) is the tree diameter at breast height (1.3 m). z_0 is the aerodynamic roughness (m), d is the zero-plane displacement (m), and $k = 0.4$ (von Karman constant). f_{CW} is a factor to account for the additional moment provided by the overhanging displaced mass of the canopy; f_{knot} is a factor to reduce wood strength due to the presence of knots (usually between 0.8 and 1; Ruel et al., 2010); and MOR is the green wood Modulus of Rupture (Pa) for the particular species, derived from bending tests (e.g. Lavers, 1969). SW is the weight of the bole of the tree (kg), calculated from total volume equations (e.g. Fonweban et al., 2012) multiplied by an average green density value (typically 850–1000 kg m^{-3}); C_{reg} (Nm kg^{-1}) is a coefficient obtained from tree pulling experiments and is a function of species, soil type and rooting depth (see Nicoll et al., 2006). D (m) is the average spacing between trees and ρ is air density (kg m^{-3}). The gust factor G is derived from the wind tunnel experiments of Gardiner et al. (1997):

$$G = [(-2.1\cdot D/h + 0.91)\cdot x/h + (1.0611\cdot \ln(D/h) + 4.2)]\cdot gfadj \tag{7}$$

where x is the distance from the forest edge (m), and the factor $gfadj = 1.5$ was used in order to give agreement with the values from the field measurements of gust factors in Blackburn (1997). Note that it is necessary to ensure that $-2.1.D/h + 0.91 \geq 0$.

The CWSs then need to be converted to the corresponding wind speeds at 10 m above the zero plane displacement ($u(d+10)_{crit}$) in order to utilise meteorological data to calculate probabilities of occurrence and return periods, or in this case to compare with the predicted above-canopy wind speed for each sub-compartment from WAsP (*Wind_WAsP*) or DAMS (*Wind_DAMS*; Equation (4)):

$$u(d+10)_{crit} = u(h)_{crit}\cdot\frac{\ln\left(\frac{10}{z_0}\right)}{\ln\left(\frac{h-d}{z_0}\right)} \tag{8}$$

where $u(h)_{crit}$ is either $u(h)_{crit\_over}$ or $u(h)_{crit\_break}$.

2.5.2. ForestGALES 2.3, gust factor adjustment = 1 [FG2.3gfadj=1]

This version of the model is identical to that described above, but the multiplier of 1.5 applied to the calculation of the gust factor has been removed (i.e. set $gfadj = 1$ in Equation (7)), in line with the more recent field measurements of Wellpott (2008) and Hale (unpublished analysis of data from the experimental measurements reported in Hale et al., 2012). These more recent measurements indicated that the earlier estimates of gust factor by Blackburn (1997) were too large and the original wind tunnel estimates of gust factor (Gardiner et al., 1997) were accurate. Therefore, there is no justification for the adjustment ($gfadj = 1.5$) that was previously made.

2.5.3. ForestGALES-TMC [FG-TMC]

The two versions of ForestGALES described above are designed for use in even-aged stands, where all trees are equal to the mean tree. A new methodology has been developed that has the potential for calculating wind loading on trees of all sizes in forest stands of mixed structure. A turning moment coefficient was defined (T_C), which directly relates the maximum applied turning moment of a tree that occurs in response to the mean wind speed at the canopy top (Hale et al., 2012; Wellpott, 2008).

$$M_{appl\_\max} = T_C\cdot u(h)^2 \tag{9}$$

where $M_{\mathrm{appl\_max}}$ is the maximum applied turning moment (Nm), T_C is the turning moment coefficient (kg) and $u(h)$ is again the wind speed at the top of the canopy (m s^{-1}). T_C was found to be very well correlated with tree size ($R^2 = 0.945$):

$$T_C = 111.7\cdot dbh^2 h \tag{10}$$

where dbh and h are diameter at breast height and tree height in metres as above. Note that the regression value published in Hale et al. (2012) of 117.3 is incorrect and it should be 111.7.

There are two immediate advantages of this methodology: firstly, the need for the gust factor is removed and secondly, in irregular stands there is a relationship between T_C and local competition, which enables the impact of thinning around individual trees to be modelled (Hale et al., 2012; Seidl et al., 2014; Wellpott, 2008).

The CWSs calculated using the turning moment coefficient approach are given in an analogous form to Equations (5) and (6) as follows (see online supplement for full derivation):

$$u(h)_{crit\_over\_TMC} = \left[\frac{C_{reg}SW}{111.7\cdot dbh^2 h}\right]^{\frac{1}{2}}\left[\frac{1}{1.136}\right]^{\frac{1}{2}}\left[\frac{1}{TMC\_Ratio}\right]^{\frac{1}{2}} \tag{11}$$

$$u(h)_{crit\_break\_TMC} = \left[\frac{\pi\cdot MOR\cdot d_0^3}{32\cdot 111.7\cdot dbh^2 h}\right]^{\frac{1}{2}}\left[\frac{f_{knot}}{1.136}\right]^{\frac{1}{2}}\left[\frac{1}{TMC\_Ratio}\right]^{\frac{1}{2}} \tag{12}$$

where f_{knot}, C_{reg}, SW and MOR are as defined for Equations (5) and (6). Note that tree diameter at the tree base (d_0) is used rather than dbh in the numerator as was the case in Equation (6), because we can only calculate the turning moment at the base of the tree with this method. An interpolated value of d_0 based on the assumption that there is a constant stress in the stem (Morgan and Cannell, 1994) is used rather than a value derived from a detailed taper equation (e.g. Fonweban et al., 2011) to ensure that the CWS is the same for breakage at tree base and at breast height (1.3 m). The CWSs are adjusted to 10 m above the zero plane displacement using Equation (8), in the same manner as for FG2.3 and FG2.3gfadj=1.

The relationships between maximum turning moment and mean wind speed (Equation (9)), and between T_C and tree size were parameterised in stands that had not been recently thinned, and were therefore acclimated to their wind environment. For a simulation in uniform stands, use of the equations as described would result in the same CWS after thinning as before thinning, because T_C is calculated from tree size alone. In reality, the wind loading on a tree is likely to be increased following a thinning, as shelter from neighbours is reduced (Albrecht et al., 2012; Gardiner et al., 1997; Papesch, 1984; Wallentin and Nilsson, 2014). The variable *TMC_Ratio* is used to account for this change in wind loading following a thinning and is given by:

$$TMC\_Ratio = 0.99\cdot Spacing\_Ratio \tag{13}$$

where *Spacing_Ratio* is the ratio of average tree spacing after and before thinning. This empirical expression was derived by comparing the detailed iterative derivation of *TMC_Ratio* against *Spacing_Ratio* for the full range of British yield models (Edwards and Christie, 1981) for the species of interest (see the online supplement for full details). The *TMC_Ratio* is applicable to a stand immediately after thinning, and we assume that it tends towards its acclimated value ($TMC\_Ratio = 1$) with time. There is some information on the acclimation of trees (e.g. Mitchell, 2000; Ruel et al., 2003) following thinning, and studies of wind damage following storm events, suggesting that stands thinned within five years have a higher probability of damage than unthinned stands (Persson, 1975; Valinger and Fridman, 2011). We assumed, therefore, that five years after thinning a stand would be acclimated to the new conditions (i.e. $TMC\_Ratio = 1$ again), which ties in to the five yearly increment of the yield tables (Edwards and Christie, 1981) used in this paper. For stands thinned within five years *TMC_Ratio* was scaled linearly between the TMC_Ratio calculated from Equation (13) immediately following thinning, and a value of 1 at five years.

2.6. ForestGALES damage prediction

The current version of ForestGALES (Gardiner et al., 2000) is designed for uniform, even-aged, single-species stands, in which all trees are assumed equal to the mean tree. It predicts either damage or no damage, i.e. there is no gradation in severity of damage predicted. There are three prerequisites to enable a validation to be done:

1. Stand characteristics at the time of the storm are required, to enable CWS to be calculated.
2. An estimation of the above-canopy wind speed during the storm is needed, to compare against these CWSs, to assess whether or not damage would be predicted by the model.
3. An assessment of actual damage to compare against the predicted damage, to evaluate the accuracy of the model predictions.

Based on the validation data set, input files were prepared for the three versions of ForestGALES. For the remainder of this paper the versions are referred to as FG2.3 (equivalent to the current release), FG2.3gfadj=1 (FG2.3 with the gust factor adjustment removed), and FG-TMC (the new method, based on the turning moment coefficient). Each of these versions was run on the validation data set to produce a CWS for each SC. In each case this CWS was compared with the above-canopy wind speed that occurred above each SC during the storm, as estimated by WAsP and DAMS (*Wind_WAsP* and *Wind_DAMS*, respectively). If the above-canopy wind speed exceeded the CWS, ForestGALES was taken to predict damage for that SC; otherwise damage was not predicted.

2.7. Logistic model

To help identify the explanatory variables associated with the wind damage across Cowal and Trossachs Forest District as a result of the storm, and to compare the accuracy of the hybrid-mechanistic approach of ForestGALES above to a purely statistical model, we developed a logistic regression model similar to Albrecht et al. (2012) and Valinger and Fridman (2011).

Because the data set was dominated by Sitka spruce stands less than 60 years old, we developed a logistic model for Sitka spruce alone and for all species combined, in order to properly separate out any potential effects of species and age. Analyses were used to test whether the following explanatory variables were statistically significant for predicting damage: age, *dbh*, top height, spacing, yield class (*YC*), C_{reg} (resistance to overturning derived from soil type and rooting depth; see Equations (5) and (11)), $f_{\text{knot}}{}^{*}MOR$ (resistance to breaking; see Equations (6) and (12)), *Wind_WAsP* and *Wind_DAMS*, and elevation. For the model based on all species combined, an additional variable defining tree species was included in the candidate set of explanatory variables. These variables were selected as they all potentially influence the resistance of a tree to wind damage and they are all variables used in the ForestGALES model.

For the development of the logistic regression model the basic approach was as follows:

(i) Using the explanatory variables above, a decision (profit) matrix was created for the target variable, in this case 'damage' (any damage recorded in a SC). Decision weights were allocated using inverse prior probabilities. For example, if 2% of the dataset was damaged and 98% undamaged the profit for estimating a damaged record correctly would be 50 units (1/0.02), and he profit for correctly identifying an undamaged record would be 1.02 units (1/0.98). Incorrect decisions were valued to be worth 0 units of profit. For this type of profit matrix, the average *Profit Score* would be 2.0 if all damaged and undamaged stands were correctly predicted by the logistic regression model. This is in contrast to an estimated average *Profit Score* of just 1.0 if SCs were selected at random and predicted to be either damaged or undamaged.
(ii) The data were partitioned into a training (60%) and a validation (40%) dataset. This random allocation of data records was stratified by the target variable 'damage' to ensure that records with damage and no damage were allocated in the same proportions to both the training and validation datasets.
(iii) A stepwise logistic regression analysis was done. The selected model was chosen from the step that produced the largest total *Profit Score* for the validation dataset.
(iv) The probability of damage for a sub-compartment (e.g. Valinger and Fridman, 2011) was predicted by:

$$p = \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3)/[1 + \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3)] \tag{14}$$

where $\beta_0,\ldots,\beta_3$ are parameters to be determined and $x_0,\ldots,x_3$ are the explanatory variables from the selected step.

2.8. Tree classification model

We conducted a similar analysis to the logistic regression using a Tree Classification model. The methodology and results are presented in the online supplement.

2.9. Model comparison and testing

2.9.1. Contingency tables

Contingency tables (see e.g. Fig. 4 in Bennett et al., 2013) are a way of comparing model damage predictions against actual damage data. We used contingency tables to see how the ForestGALES and the logistic model predictions changed with adjustment of specified thresholds. For ForestGALES we systematically modified the calculated CWS by multiplying by a factor varying between 0 and 200 % (i.e. we systematically varied the outputs of the model in order to change the thresholds) and keeping the predictions of above-canopy wind speed (*Wind_DAMS* and *Wind_WAsP*) fixed. It was done in this manner because ForestGALES is the model of interest, and WAsP and DAMS have been already been validated in previous studies (e.g. Suárez et al., 1999). For the logistic model we varied the model probability threshold for damage from 0 to 100 %.

From the contingency tables it is possible to derive a number of measures of model performance (see Table 3 in Bennett et al., 2013 for more information). The *Sensitivity* (Equation (15)) (probability of detection, or hit rate) represents the proportion of damaged SCs that are correctly predicted. This measure ignores false alarms:

$$Sensitivity = \frac{Hits}{Observed\ Yes} \tag{15}$$

Specificity (Equation (16)) represents the proportion of undamaged SCs that are correctly predicted. This was then used to calculate the false alarm rate:

$$Specificity = \frac{Correct\ Negatives}{Observed\ No} \tag{16}$$

$$False\ Alarm\ Rate = 1 - Specificity \tag{17}$$

If CWS is decreased (i.e. more damage predicted), *Sensitivity* will increase (more hits), but *Specificity* will decrease (more false alarms). *Accuracy* (Equation (18)) provides a measure of the total number of correct predictions (damage or no damage):

$$Accuracy = \frac{Hits + Correct\ Negatives}{Total} \tag{18}$$

As *Accuracy* is heavily influenced by the most common category (in this case, no damage), it was only calculated at the point where *Sensitivity* = *Specificity* (Hosmer and Lemeshow, 2000). This is the point where the multiplication factor applied to the CWSs gives the same percentage of correctly identified damaged and undamaged stands and is referred to as the cutpoint.

The *Success Index* (Equation (19)) equally weights the model detection of damage and no damage:

$$Success\ Index = \frac{1}{2}\left(\frac{Hits}{Observed\ Yes} + \frac{Correct\ Negatives}{Observed\ No}\right) = \frac{1}{2}(Sensitivity + Specificity) \tag{19}$$

The *Success index* multiplied by 2 gives a *Profit Score* (Equation (20)) which is exactly equivalent to that obtained from the development of the logistic regression model described in Section 2.7. In this way we were able to determine a *Profit Score* for ForestGALES to enable direct comparison with the logistic model.

$$Profit\ Score = 2{*}Success\ Index \tag{20}$$

Model bias measures the ratio of modelled to observed damage occurrence, with values <1 suggesting the model underestimates damage and values >1 suggesting it overestimates. *Bias score* was calculated using:

$$Bias\ Score = \frac{Hits + False\ Alarms}{Hits + Misses} = \frac{Modelled\ Yes}{Observed\ Yes} \tag{21}$$

2.9.2. Receiver operator curves

Receiver Operating Characteristics (ROC) and Area under the ROC curves (*AUC*) were employed in order to test how well the models discriminated between damaged and undamaged stands. The ROC is obtained by plotting *Sensitivity* against the *False Alarm Rate* (1-*Specificity*). The *AUC* was then calculated as the area under the curve using the trapezoid rule. An *AUC* of 0.5 suggests no model discrimination, more than 0.7 is considered as acceptable discrimination and more than 0.8 as excellent discrimination (Hosmer and Lemeshow, 2000).

ROC and *AUC* analysis was done for the three versions of ForestGALES with the two estimations of above-canopy wind speed (*Wind_DAMS* and *Wind_WAsP*). It was also done for the training and validation data sets for the logistic regression, again using both *Wind_DAMS* and *Wind_WAsP*. This gave a total of 10 model scenarios. All analyses and model testing were done using SAS Enterprise Miner 7.1 (SAS Institute, Cary NC, USA) or Matlab 2014a (Mathworks, Natick MA, USA).

3. Results

3.1. Above-canopy wind speed

For both methods of calculating the wind speed over the SCs a single value of wind speed was attributed to each SC; these are compared in Table 5. Although the wind speeds from WAsP and from DAMS were on average very similar (<1 m s^{-1} difference on average), the distribution was different from the two methods with WAsP giving a larger range of wind speed values compared with DAMS.

3.2. ForestGALES

3.2.1. Critical wind speed

CWSs from FG2.3 were generally in the range 20–40 m s^{-1} (Table 6). Removing the adjustment in the gust factor calculation (i.e. using FG2.3gfadj=1) gave a corresponding increase in CWS values of about 20%. CWSs from the new method of calculation

Table 5
Estimated above-canopy wind speeds (m s^{-1}) from WAsP and DAMS, for all SCs in the validation data set.

Wind speed (m s^{-1})	5th %-ile	1st Quartile	Mean	3rd Quartile	95th %-ile
WAsP	10.5	16.2	20.4	23.7	31.9
DAMS	13.8	16.6	19.7	22.1	28.1

Table 6
Critical wind speed (CWS) from the three versions of ForestGALES, for all SCs in the validation data set.

CWS (m s^{-1})	Min.	1st Qu.	Mean	3rd Qu.	Max
FG2.3	9.5	20.8	28.6	35.1	83.9
FG2.3gfadj=1	10.9	25.1	34.7	43.0	102.8
FG-TMC	10.5	26.4	35.1	43.3	100.0

used in ForestGALES-TMC were overall very similar to those from FG2.3gfadj=1.

3.2.2. Damage predicted by ForestGALES

The three versions of ForestGALES, with no adjustment to calculated CWSs, predicted damage ranging from 195 SCs to 1698 SCs (representing 3%–24% of the validation data set; Table 7). The predicted number of damaged SCs using *Wind_WAsP* were substantially higher than those using *Wind_DAMS*, despite the calculated wind speeds from WAsP being only about 1 m s^{-1} higher on average (see Section 3.1 above). Predicted damage from FG2.3 was higher than from either FG2.3gfadj=1 or FG-TMC. There was generally good agreement between FG2.3gfadj=1 and FG-TMC in the number of SCs with damage predicted and when coupled with *Wind_DAMS* these two models predicted damage in 3–4 % of SCs, which is close to the observed levels of damage (2% of SCs). For comparison the WHC, which many British foresters still use, would have predicted terminal damage (>40% damage) to 1805 SCs (26%) in the validation data set. This comparison of WHC with observed storm damage across a whole district supports other indications that it tends to over-predict damage (Mason and Quine, 1995; Quine, 1994; Quine and Bell, 1998).

3.2.3. Species and age differences

We compared predicted damage against observed damage in the study area as a function of species and age. Results are presented based on only FG2.3gfadj=1 and FG-TMC together with *Wind_DAMS* because these combinations predicted overall levels of damage closest to observed levels. Furthermore, using WAsP to estimate wind speed is a time-consuming method, due to both acquiring and formatting the input data, and the actual processing time. In contrast, DAMS uses the data set that is operationally used within ForestGALES to represent the windiness of the site, and the data are readily available within the Forestry Commission SCDB.

FG2.3gfadj=1 and FG-TMC predicted damage in a similar number of SCs, but not necessarily in the same SCs; there was approximately 60% overlap between them (Fig. 1). FG2.3gfadj=1 captured well the vulnerability of Sitka spruce and the stability of Scots pine, but underestimated the vulnerability of Norway spruce and overemphasised the vulnerability of lodgepole pine and the larches. FG-TMC predicted well the damage to hybrid larch, lodgepole pine and Norway spruce, but underestimated the vulnerability of Sitka spruce and overemphasised the vulnerability of Japanese larch, European larch and Scots pine. Both models overpredicted the low observed damage for Douglas-fir and western hemlock. Although there were few SCs against which to compare damage, both models reproduced the observed stability of Corsican pine, grand fir and noble fir. In summary, neither model reproduced exactly the actual damage as a function of species, with the most important discrepancies being between Sitka spruce, Scots pine and the larch species.

Both versions of ForestGALES predicted less damage in younger stands than was observed (Table 8); this was most pronounced with FG-TMC. Neither of the models reproduced the disproportionate damage to stands in the 30–50 year-old age class. The fact that damage was predicted more for older stands is not an artefact of the age-class distribution of different species within the forest. The forest was dominated by Sitka spruce stands, the majority of which were less than 50 years old, and which constituted two-thirds of the damaged SCs. The tendency of the models to predict damage to older stands was confirmed by running dummy data sets through FG2.3gfadj=1 and FG-TMC for a range of species, using the same age-class distribution for each. In all cases, the average age of stands with damage predicted was substantially higher (~20 years) than those where damage was not predicted; whereas for the observed damage the average age was similar for damaged and undamaged stands (Table 8).

The species differences between the model predictions and observed damage may be in part an artefact of the fact that FG2.3gfadj=1 and FG-TMC over-predicted damage to older stands. For example, the majority of European larch stands in the study area were aged 50–100 years, which corresponds with the age range where FG2.3gfadj=1 and FG-TMC were most likely to predict damage; this could account for the overprediction of damage to European larch. However, this does not hold for Norway spruce and Scots pine, both of which were dominated by stands aged 50–90 years old, but for which there was no consistent over-prediction by the models. Unfortunately, there are insufficient data in this study to do a formal statistical analysis of the interaction between age and species.

3.2.4. Sensitivity of predictions

Very small differences in wind speed (either the estimated above-canopy wind speed or CWS) can make the difference between damage being predicted or not predicted. Looking only at those SCs where FG2.3gfadj=1 and FG-TMC gave different predictions (i.e. one or other predicted damage, but not both), we looked at the difference between the calculated critical speeds and the above-canopy wind speed. If one of the CWS values was close to the above-canopy wind speed, then a small change could bring agreement between the models in their prediction of damage (or no damage) for that SC. In fact, as shown in Fig. 2a, for the 195 SCs for which damage was predicted by either FG2.3gfadj=1 **or** FG-TMC, a change in CWS (or above-canopy wind speed) of ≤1 m s^{-1} could bring agreement between the models for over 70% of these stands (Fig. 2b). The differences in predicted damage by species shown in Fig. 1 for FG2.3gfadj=1 and FG-TMC can be mainly attributed to these small differences in calculation of CWS.

3.3. Logistic regression

3.3.1. Sitka spruce

The logistic regression analysis using *Wind_DAMS* as an explanatory variable for observed damage gave *Wind_DAMS*, top height and elevation as the only significant factors, with increasing probability of damage with **increasing** *Wind_DAMS* and top height and **decreasing** elevation (Table 9). Using *Wind_WAsP* as an explanatory variable gave *Wind_WAsP*, age, top height and YC as the significant factors with increasing probability of damage with **increasing** *Wind_WAsP* and top height and **decreasing** YC and age (Table 10). A quantitative assessment of the performance of the

Table 7
Number of sub-compartments (percentage in brackets) with damage predicted by the three versions of ForestGALES, and two methods of estimating above-canopy wind speed during the storm.

Wind speed model	FG2.3	FG2.3gfadj=1	FG-TMC
WAsP	1698 (24)	762 (11)	598 (9)
DAMS	1054 (15)	280 (4)	195 (3)

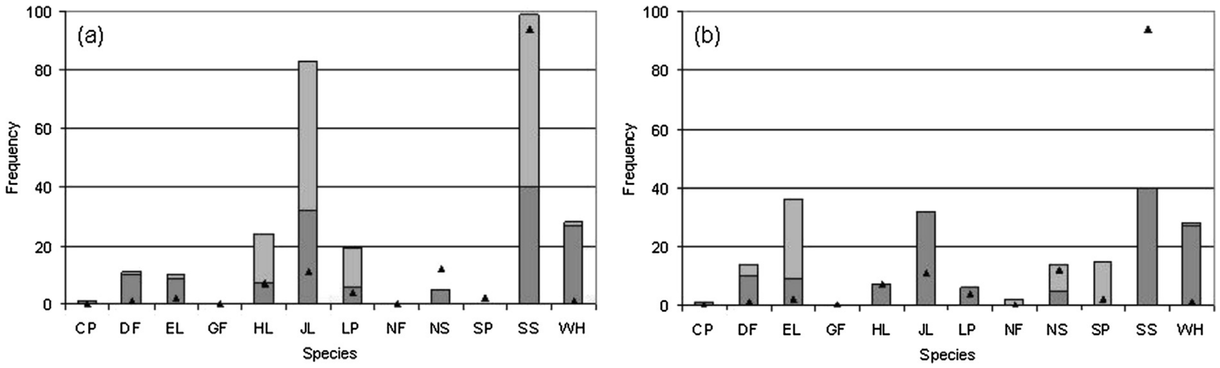

Fig. 1. Predicted damage by species, for (a) FG2.3gfadj=1 and (b) FG-TMC, based on above-canopy wind speed from DAMS. The lower portion of each bar (darker grey) represents SCs where both models predicted damage; the upper part shows where the models differed. The black triangles show the number of SCs with observed damage. See Table 1 for species codes.

Table 8
Summary of age in years for observed damaged and undamaged SCs, and the ages of predicted damaged and undamaged stands from FG2.3gfadj=1 and FG-TMC. Undamaged stands all have similar age distributions whereas damaged stands are older in the ForestGALES predictions.

	Min.	1st Qu.	Mean	3rd Qu.	Max.
Damage observed	14	35	43	49	75
No damage observed	2	23	41	58	162
FG2.3gfadj=1 predicts damage	22	52	62	72	151
FG2.3gfadj=1 predicts NO damage	2	23	41	57	162
FG-TMC predicts damage	36	59	68	76	151
FG-TMC predicts NO damage	2	23	41	57	162

logistic regression model, using the *Profit Scores*, is presented together with ForestGALES in Section 3.4 below.

3.3.2. All species

With all species included, the logistic regression using *Wind_DAMS* as an explanatory variable gave only *Wind_DAMS* and elevation as significant factors for predicting damage, with once again increasing probability of damage with **increasing** *Wind_DAMS* and **decreasing** elevation (Table 11). Using *Wind_WAsP* as an explanatory variable gave *Wind_WAsP*, age and top height as significant factors, with increasing probability of damage with **increasing** *Wind_WAsP* and top height and **decreasing** age (Table 12).

3.4. Model evaluation and comparison

3.4.1. Receiver operator curves

The receiver operator curves for all species using the six combinations of ForestGALES with *Wind_WAsP* and *Wind_DAMS* are

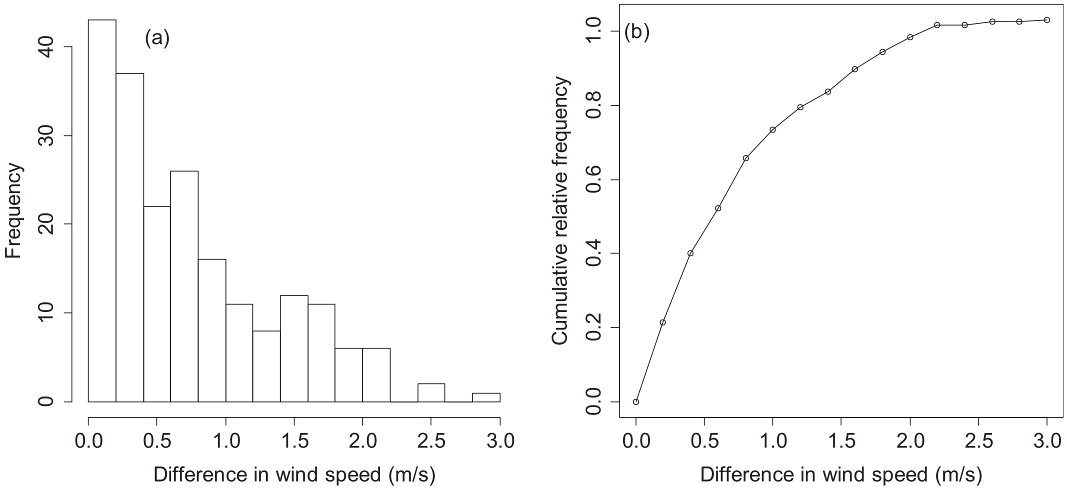

Fig. 2. a) The minimum difference between critical and above-canopy wind speed for SCs with damage predicted ONLY by FG2.3gfadj=1 OR by FG-TMC. b) The level of agreement between models as a function of difference in predicted wind speed (value of 1.0 in cumulative relative frequency means full agreement).

Table 9
Logistic model fit using *Wind_DAMS* for Sitka spruce only.

Parameter	DF	Estimate	Standard error	Wald chi-square	Pr > chisq	Standardised estimate	Exp (Est)
Intercept	1	−9.9209	1.0141	95.7	<0.0001		0
Elevation	1	−0.0101	0.00233	18.97	<0.0001	−0.5432	0.99
Top height	1	0.0849	0.0206	17.05	<0.0001	0.3688	1.089
Wind_DAMS	1	0.304	0.0452	45.34	<0.0001	0.7532	1.355

Table 10
Logistic model fit using *Wind_WAsP* for Sitka spruce only.

Parameter	DF	Estimate	Standard error	Wald chi-square	Pr > chisq	Standardised estimate	Exp (Est)
Intercept	1	−4.2851	1.0953	15.31	<0.0001		0.014
Age	1	−0.1089	0.0317	11.79	0.0006	−1.1456	0.897
Top height	1	0.3305	0.0836	15.64	<0.0001	1.429	1.392
Wind_WAsP	1	0.0527	0.0227	5.39	0.0203	0.1812	1.054
YC	1	−0.1739	0.0822	4.47	0.0344	−0.3872	0.84

Table 11
Logistic model fit using *Wind_DAMS* for all species.

Parameter	DF	Estimate	Standard error	Wald chi-square	Pr > CHISQ	Standardised estimate	Exp (Est)
Intercept	1	−7.2563	0.5904	151.06	<0.0001		0.001
Elevation	1	−0.0101	0.00189	28.48	<0.0001	−0.5205	0.99
Wind_DAMS	1	0.2457	0.0362	45.96	<0.0001	0.5735	1.278

Table 12
Logistic model fit using *Wind_WAsP* for all species.

Parameter	DF	Estimate	Standard error	Wald chi-square	Pr > chisq	Standardized estimate	Exp (Est)
Intercept	1	−6.9874	0.5537	159.25	<0.0001		0.001
Age	1	−0.0322	0.0104	9.67	0.0019	−0.3977	0.968
Top height	1	0.1354	0.026	27.08	<0.0001	0.5791	1.145
Wind_WAsP	1	0.0857	0.017	25.33	<0.0001	0.2932	1.09

shown in Fig. 3, and for the logistic regression model in Fig. 4. The ROC curves for Sitka spruce only were very similar and these are presented in the online supplement. Differences between the ROC curves are summarised by the *AUC* values in Table 13.

From the curves it is clear that all model combinations are able to discriminate between damaged and non-damaged SCs. *AUC* values for each curve are given in Table 13. The combination of the three ForestGALES models with *Wind_WAsP* for all tree species fail to reach the 0.7 threshold by a very small margin; all the other model combinations are above 0.7. In general the model performed better using *Wind_DAMS* than *Wind_WasP*, and for Sitka spruce on its own rather than for all species combined. The three versions of ForestGALES have similar *AUC* values, which are lower than those from the logistic regression model. The highest discrimination is shown by the logistic regression model with DAMS for Sitka spruce only.

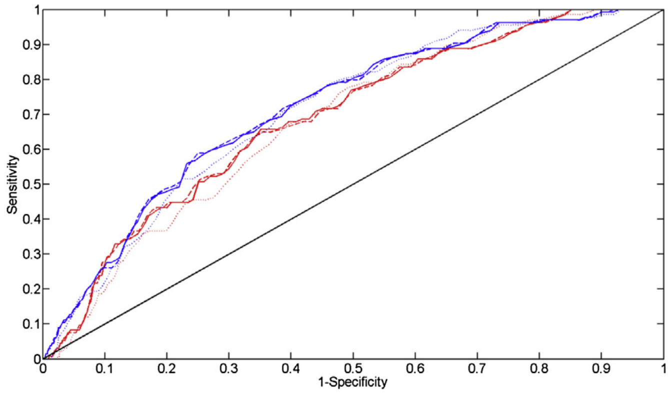

Fig. 3. Receiver operator curves for three versions of ForestGALES with two airflow models (DAMS and WAsP) for all species (Sitka spruce only curves are presented in the online supplement). Red is with WAsP, blue is with DAMS, black is baseline. Solid lines are FG2.3, dashed lines are FG2.3gfadj=1, dotted lines are FG-TMC.

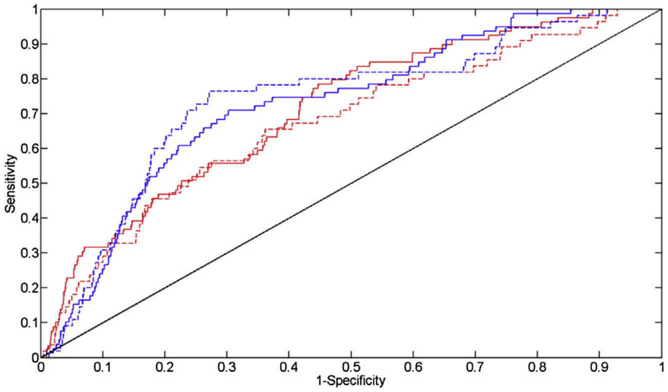

Fig. 4. Receiver operator curves for logistic regression model for training and validation data with two airflow models (DAMS and WAsP) for all species (Sitka spruce only curves are presented in the online supplement). Red is with WAsP, blue is with DAMS, black is baseline. Solid lines are training data, dashed lines are validation data.

Table 13
Area under the ROC curves for all model combinations for Sitka spruce only and for all species combined.

Model	*AUC* (Sitka spruce only)	*AUC* (all species)
FG2.3 & WAsP	0.71	0.69
FG2.3gfadj=1 & WAsP	0.71	0.69
FG-TMC & WAsP	0.71	0.68
FG2.3 & DAMS	0.73	0.72
FG2.3gfadj=1 & DAMS	0.73	0.72
FG-TMC & DAMS	0.74	0.71
Logistic regression & WAsP: training	0.72	0.71
Logistic regression & WAsP: validation	0.75	0.67
Logistic regression & DAMS: training	0.79	0.73
Logistic regression & DAMS: validation	0.79	0.74

Table 14
Accuracy, *Bias* and *Profit Score* of models for Sitka spruce only.

Model	*Accuracy* at cutpoint	*Bias Score*	*Bias Score* at cutpoint	*Profit Score*	*Profit Score* at cutpoint	Multiplier at cutpoint
FG2.3 & WAsP	0.66	8.1	14.7	1.24	1.32	0.88
FG2.3gfadj=1 & WAsP	0.65	3.3	15.1	1.2	1.30	0.73
FG-TMC & WAsP	0.67	2.4	14.5	1.08	1.32	0.70
FG2.3 & DAMS	0.68	5.1	14.1	1.24	1.34	0.84
FG2.3gfadj=1 & DAMS	0.68	1.1	14.2	1.10	1.36	0.70
FG-TMC & DAMS	0.70	0.4	13.1	1.04	1.36	0.68
LR & WAsP: training	0.66		15.1		1.31	
LR & WAsP: validation	0.69		13.1		1.38	
LR & DAMS: training	0.78		10.0		1.53	
LR & DAMS: validation	0.73		12.0		1.46	

Table 15
Accuracy, *Bias* and *Profit Score* of models for all species.

Model	*Accuracy* at cutpoint	*Bias Score*	*Bias Score* at cutpoint	*Profit Score*	*Profit Score* at cutpoint	Multiplier at cutpoint
FG2.3 & WAsP	0.66	11.9	17.9	1.22	1.28	0.84
FG2.3gfadj=1 & WAsP	0.66	5.2	17.9	1.18	1.30	0.69
FG-TMC & WAsP	0.64	4.5	19.1	1.08	1.24	0.68
FG2.3 & DAMS	0.66	7.9	18.0	1.24	1.32	0.82
FG2.3gfadj=1 & DAMS	0.67	2.1	17.6	1.08	1.32	0.68
FG-TMC & DAMS	0.65	1.5	18.4	1.04	1.30	0.67
LR & WAsP: training	0.63		19.7		1.27	
LR & WAsP: validation	0.64		18.7		1.29	
LR & DAMS: training	0.70		16.4		1.41	
LR & DAMS: validation	0.73		14.3		1.49	

3.4.2. Model accuracy, bias and profit

The different measures of model performance presented in Section 2.9 are given in Table 14 and Table 15 for predictions of damage for Sitka spruce only and for all species, respectively. For ForestGALES, *Profit* and *Bias Scores* were obtained for the unadjusted CWS values and at the cutpoint where *Sensitivity* and *Specificity* were identical. *Accuracy* was calculated only for the cutpoint. The value of multiplier at the cutpoint is also shown. Non-cutpoint values are not provided for the logistic regression model because it was deliberately tuned to the cutpoint (i.e. highest *Profit Score*; see Section 2.7).

For Sitka spruce the *Accuracy* and *Profit Score* values range from 0.65 to 0.78 and 1.30 to 1.53, respectively, and for all species they range from 0.64 to 0.73 and 1.24 to 1.49, respectively. All models perform better with *Wind_DAMS* than *Wind_WAsP*. If we compare models using DAMS, the logistic regression model generally has higher *Accuracy* and *Profit Score* values than ForestGALES, and both types of model are slightly more accurate for the Sitka spruce data only compared with the data for all species.

For ForestGALES, although *Profit Scores* are highest at the cutpoint, the *Bias Score* is much higher at the cutpoint than with a multiplier of 1 (no adjustment to the CWS), i.e. with an increase in overall successful predictions comes an increase in false alarms. For example, *Bias Scores* for Sitka spruce range from 13.1 to 15.1 at the cutpoint to 0.4 to 8.1 with no adjustment. The *Bias Score* for the logistic regression model varies from 10.0 to 15.1 and 14.3 to 19.7 for Sitka spruce and all species, respectively. Therefore, high *Accuracy* and a high *Profit Score* can only be obtained by over-predicting damage by a large value (up to 19.1 times the observed amount), which for ForestGALES is achieved by reducing the calculated CWSs (by multipliers of 0.67–0.88). The least biased models are FG2.3gfadj=1 and FG-TMC, using *Wind_DAMS* with no adjustment, for both Sitka spruce and all species. These models are biased, respectively, by factors of 1.1 (almost perfect balance between damage and no damage) and 0.4 (under prediction of damage) for Sitka spruce, and over-predict damage by factors of 2.1 and 1.5 for all species combined.

4. Discussion

4.1. Observed damage

Experience and analysis of damage from many storm events have shown tree height to be the most consistent factor contributing to wind damage in a forest. All else being equal, therefore, one might expect taller (older) trees to be damaged preferentially to smaller (younger) trees. In the storm event studied here, this was not the case: there was no damage in older stands (80–160 years), and stands in the 30–50 year old age classes were damaged disproportionately to their occurrence. The lack of damage in older stands may be a direct consequence of forest management practices, with older stands being retained in sheltered areas with better soils where they are less prone to damaging winds. It may also be that the older stands have weathered strong winds in the past and the weaker stems will have been removed already, and those remaining will have acclimated to strong winds. Quine (1995) suggested that there might come a point in the lifetime of a stand where vulnerability levels off with age, due to ongoing acclimation and a lower height to diameter ratio. This is consistent with the observations of Valinger and Fridman (2011) who found that stands older than 110 years were at less risk of damage than younger stands following storm Gudrun in southern Sweden.

The disproportionate damage to younger stands can in part be attributed to recent thinnings, and to stands that had a late first thinning (J. Hair, Forestry Commission, pers. comm.). However, there was also unexpected damage to younger, unthinned and relatively stable stands. This reflects the extremely localised effects of variations in wind speed during a storm. Usbeck et al. (2012) found that wind gust speed at the surface was the most important factor leading to damage and dominated all other factors, but found it very difficult to correlate wind speeds directly with damage to particular stands. Schütz et al. (2006) and Albrecht et al. (2012) also could not find a correlation between damage and measured wind speeds; this is probably a reflection of the spatial resolution of the measurements or model simulations used, and points to the extremely local variability in wind speeds during storms (Boose et al., 1994).

4.2. Logistic regression models

The logistic regression models provided acceptable discrimination between damaged and undamaged stands (except for the all species validation data, using *Wind_WAsP*), with the best results using *Wind_DAMS* for Sitka spruce only. The lack of discrimination for the all species validation data using *Wind_WASP* may result from variation in stability between species, which is not captured by the model. The better performance using *Wind_DAMS* may be because the DAMS system was developed with data from predominantly this type of upland forested location (Quine and White, 1993). The models indicated that increases in wind speed and tree top height were associated with increased risk of damage. This fits with the general findings from earlier analyses of storm damage (Colin et al., 2009; Gardiner et al., 2013; Hanewinkel et al., 2011) and with previous calculations using ForestGALES (Gardiner et al., 2000, 2008). However, there were confounding influences of tree age, YC and elevation, which make the overall story more complicated. Interestingly, tree height and age appeared to work in opposite directions for the models using *Wind_WasP*, with older trees being less at risk (Tables 10 and 12). The effect of elevation in the models using *Wind_DAMS* is also counterintuitive (Tables 9 and 11), with trees at higher elevations being less vulnerable than trees at lower elevations (all other things being equal). Albrecht et al. (2012) also observed that decreasing topographic shelter was associated with lower damage. Again this suggests that trees regularly exposed to higher winds may be better acclimated to their wind environment, having allocated proportionally more of the available assimilates to their roots, thereby increasing their overall stability (Nicoll and Ray, 1996; Nicoll et al., 2008).

The comprehensive review in Usbeck et al. (2012) of previous statistical modelling of the factors leading to wind damage in forests shows how difficult it is to ascribe particular stand, tree or meteorological factors to enhanced stand vulnerability. There can often be conflicting evidence for the importance of a particular factor, with the relative importance of tree characteristics often very dependent on the exact site conditions, e.g. soil type and drainage (Bélouard et al., 2012). Recent work by Albrecht et al. (2013) found no difference in the vulnerability of Douglas-fir and Norway spruce even though earlier work had suggested Douglas-fir was probably less vulnerable (Schmidt et al., 2010). Recent review studies have concluded that the most consistent factors to predisposing forest stands to wind damage are tree height, recent thinnings (approximately within the previous 5 years; Lagergren et al., 2012; Valinger and Fridman, 2011) and saturated soils (Colin et al., 2009; Hanewinkel et al., 2013).

Finally, although the statistical analyses showed the logistic model generally performed better than ForestGALES in terms of *Accuracy* and *Profit Score*, it must be remembered that it was developed only using data from the study area and one storm event; it may not perform as well in other scenarios.

4.3. ForestGALES models

All three versions of ForestGALES were able to successfully discriminate between damaged and undamaged stands when used with *Wind_DAMS*. However, to maximise *Accuracy* and the *Profit Score* it was necessary to reduce the predicted CWSs by between 67 and 88 % (Tables 14 and 15). The result is to over-predict the number of damaged stands and to introduce high levels of bias. When the model predictions of CWS were not adjusted the ability to predict the stands that were damaged was reduced, but the bias was also reduced. The highest bias was always for FG2.3, which supports previous evidence that it is pessimistic in its predictions of damage (Gardiner et al., 2008), i.e. it predicts damage to more forest stands than is observed. The close agreement between FG2.3gfadj=1 and FG-TMC, and the fact that these two models more closely replicated the observed levels of damage, indicate that the over-pessimism of FG2.3 was due, at least in part, to the adjustment that was made to the gust factor calculations when the model was originally developed. The good predictions of overall damage levels compared with that observed (low *Bias Score*) when using FG2.3gfadj=1 and FG-TMC (two very different wind risk calculation methods) coupled with two very different airflow models (DAMS and WAsP), indicate that both new versions of ForestGALES represent an improvement over the current model (FG2.3) for predicting overall damage across this forest, which is typical of many Sitka spruce-dominated forests in the Great Britain. It is also encouraging to see such close agreement between the TMC method and the currently-accepted roughness method, as the TMC method is computationally simpler. It also provides a basis for developing single-tree risk modelling within irregular forest stands, because the wind loading is based on the characteristics of each tree (Hale et al., 2012; Seidl et al., 2014).

Some of the discrepancies between FG2.3gfadj=1 and FG-TMC regarding damage predictions for different species are due to the very small differences in the predicted CWSs from the two models as discussed in Section 3.2 (<1 m s^{-1} change would bring agreement in 70% of stands currently without agreement). There are also different levels of reliability that can be placed on the regressions used for resistance to overturning (C_{reg}) for the different species because of the numbers of trees used in the tree pulling experiments and the variety of soils on which trees of a particular species were pulled (Nicoll et al., 2006). For example, there were 1155 Sitka spruce pulled on all forest soil types, whereas there were only 24 European larch pulled on a single soil type. Another factor is that the two models use different methodologies for calculating the wind loading on a tree. Drag coefficient and effective crown size are used in the iterative estimation of CWS in FG2.3gfadj=1 but not in FG-TMC. So, for example, Scots pine has a very small effective crown area, which makes it less prone to damage as calculated by FG2.3gfadj=1 in comparison to FG-TMC. To date, the TMC method has not been parameterised using Scots pine and we have assumed that the same relationship for calculating wind loading applies to all species, but this may not be the case. This highlights the need for further work on validating the TMC method for a wider range of species and forest ages.

4.4. ForestGALES limitations

One issue that needs to be addressed in future work is the fact that all three versions of ForestGALES predicted more damage in older stands than was observed. This probably reflects the fact that the ForestGALES model does not currently contain any acclimation for the trees, for example by adjusting the resistance to overturning as a function of DAMS exposure (Nicoll et al., 2008); nor does it allow for the removal of weaker trees due to previous events. The prediction of higher than observed levels of damage in older stands may also be an artefact of potential overestimation of wind speeds by DAMS and WAsP in the sheltered locations where many older stands are retained for their landscape value. The development of the DAMS scoring system had an emphasis on exposed locations (average elevation of wind monitoring sites was 300 m; Quine, 2000), as these were the main areas of concern for commercial forestry, and DAMS may, therefore, be less accurate at predicting wind speeds in more sheltered locations. Furthermore, neither WAsP nor DAMS simulates the flow separation that occurs in the lee of a hill, and both models have been shown to over-estimate the wind speed in steep terrain and valley bottoms (Suárez et al., 1999). Until there are improvements in meso-scale airflow modelling (e.g. Lopes da Costa et al., 2006), accurate prediction of damage at a stand level in complex terrain remains extremely challenging (Usbeck et al., 2012). Another possible cause for the over-prediction of damage to older stands is the accuracy of available stand data for input to the models. For older stands, yield class values in the SCDB are based on measurements made early in the rotation. If subsequent growth did not meet expectations, due for example to weed competition or lack of nutrition, then the actual top height would be less than that calculated within ForestGALES. The resulting modelled risk would be higher than the actual risk, which could contribute to the systematic over-prediction of damage to older stands.

Shortcomings in wind speed modelling and accuracy of input data also contribute to the fact that although overall the models work well at a forest scale, they cannot currently accurately predict exactly which individual SCs will be damaged during a storm. Firstly, predictions of damage are very sensitive to very small differences in either the above-canopy or CWSs, and therefore the models will incorrectly predict damage to some stands, and miss damage in other stands. Further errors would be introduced if the specified management model had not been followed: the time since thinning, spacing, or tree dimensions may be incorrect. Also, no account was taken of upwind clearfell sites, which would influence wind loading on a stand. There is an aspiration, over the coming decade, for forest districts in Scotland to populate the SCDB with measured values of *dbh*, top height and spacing for each SC, rather than representing stands in terms of management model and yield class. The use of terrestrial and airbourne LiDAR as mensurational tools would also provide an opportunity to obtain these parameters, as well as crown dimensions, giving a much improved set of input data when running ForestGALES across a forest district. Use of airborne LiDAR to provide input data for ForestGALES has already been made (Suárez et al., 2008) and shows great promise. A further factor contributing to lack of accuracy at the SC level is that many of the sub-models within ForestGALES, such as the calculation of crown characteristics and critical turning moments, are derived from simple linear algorithms for each species. Individual SCs will inevitably deviate from the regression lines for these models, resulting in discrepancy between model predictions and actual conditions. Therefore, with the input data currently available (e.g. from the SCDB) such models are most suitable for use at the forest scale for management guidance, rather than as a predictive tool at stand level. However, this could change if both better airflow models and improved input data (e.g. from airborne LiDAR) become available.

4.5. Implications for forest management

The results from this paper suggest that the ForestGALES model with the DAMS wind score system is able to acceptably discriminate between damaged and undamaged stands using input data from the Forestry Commission SCDB. However, there is a trade-off between high levels of accuracy and high levels of bias. To most accurately identify the stands likely to be damaged it is necessary to reduce the predicted CWSs (effectively to increase the vulnerability of all stands) but this would mean a large over-prediction of the likely levels of damage at a forest scale. For normal forest management, FG2.3gfadj=1 and FG-TMC appear to be the most appropriate versions of ForestGALES due to their low bias. They can be used as part of a decision support system by forest managers to understand the overall impact of forest management (e.g. Andersson et al., 2014; Ray et al., 2014) and to form the basis of any forest wind risk mitigation strategy (Gardiner and Quine, 2000; Gardiner and Welton, 2013; Schelhaas et al., 2010). They can also help forest ecologists to predict the occurrence and spread of wind damage in forests at the landscape level (see e.g. Seidl et al., 2014).

4.6. Future work on forest wind risk modelling

There have to date been two approaches to wind risk modelling: empirical (based on observed damage) and hybrid mechanistic-empirical (based on solving physical equations). Although empirical models such as the logistic regression model in this study find relationships between wind damage and stand and site characteristics, there are always problems of using them in different locations or for different storms (Lanquaye-Opoku and Mitchell, 2005). Both Valinger and Fridman (2011) and Schmidt et al. (2010) mentioned that one should not draw general conclusions from an empirical model from a single storm event. Therefore, hybrid mechanistic-empirical models such as ForestGALES provide the best possibility for developing generic wind risk models for all forest types and meteorological conditions. In addition, having two methodologies (“roughness” and TMC methods) within the model for calculating wind loading and CWS allows a basic assessment of the uncertainty in the calculation.

Extending the use of ForestGALES to more complex forest structures (mixed species and ages) is possible with the TMC method as used by Seidl et al. (2014). Nevertheless to have any possibility of predicting the risk to individual trees, improvement is required in the representation of within-forest variability in individual tree characteristics and their level of wind exposure, as it is clear that the vulnerability of individual trees is a strong function of the level of shelter from their neighbours (Wellpott, 2008). Fortunately, detailed within-stand data are now becoming more routinely available due to developments in airborne and terrestrial LiDAR systems (e.g. Dassot et al., 2011; Suárez et al., 2008) and development of these new tree-level versions of the model should be of interest to those working with more complex or natural forests.

5. Conclusions

This paper reports a comprehensive validation of the predictions of damage in a storm from three versions of ForestGALES (a hybrid mechanistic-empirical model of wind risk to forests). It also compared the ForestGALES models with a statistical logistic regression model developed from the observations of damage. The version of ForestGALES (FG2.3) currently in operational use within British forestry was found to be pessimistic in its predictions of overall levels of damage (i.e. predicted more damage than was observed). A revised version using the same methodology, and a completely new method based on individual tree characteristics, agreed well with observed damage at the forest scale and suggests that ForestGALES can be used as part of a reliable decision support system for plantation forests. However, comparison of predicted versus observed damage at the stand scale showed discrepancies with respect to both species and age class. This has highlighted a number of deficiencies in ForestGALES which need to be addressed in order to better represent the damage variation between species and with age, and if use of the model is required for other forest types (e.g. broadleaf and mixed-species forests). These requirements can be summarised as follows:

- Better representation of acclimation of trees to their local wind environment and the acclimation of stands with age due to the loss of less wind-firm individual trees.
- Improvements in modelling the crown characteristics of a number of species as a function of age and growing conditions.
- More comprehensive measurements of the streamlining properties of a number of species, including broadleaves.
- Further validation of the TMC method for other species in addition to Sitka spruce and European larch.
- Tree-pulling on broadleaved species, for which data are currently almost non-existent with the exception of birch (Peltola et al., 1999).
- Improvements in modelling the wind speeds over forests during storm events in order to better predict the probability of damage.

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Author contributions: “S.H., B.G and B.N. designed the research and developed the ForestGALES model; P.T and S.P. collated, quality checked and processed the data used in the validation; A.P. conducted the statistical analysis; and S.H. and B.G. ran the model simulations, completed the comparison with observations, and wrote the manuscript.”

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.envsoft.2015.01.016

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