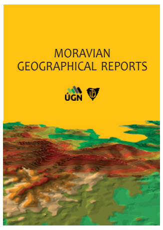

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Assessing and forecasting the influence of environmental controls on windstorm disturbances in the Central Low Tatras, through regression models

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Abstract

Nowadays, the large-scale disturbance and subsequent temporary deforestation of mountain forests are widely discussed phenomena. In this study, we built both a logistic regression model (LRM) and a generalised additive model (GAM), in order to understand the drivers of deforestation after the Elisabeth windstorm (2004) in the Central Low Tatras, Slovakia. A set of topographic and biotic characteristics was selected as explanatory variables, while the presence of deforestation was a response variable. The results show that the most prone to windstorm-driven damage are forests growing at a high elevation, in the ridge's surroundings, and on gentle slopes exposed to the wind during the disturbance. Moreover, the stands with a high proportion of Norway spruce and with medium-diameter trees, which are under forest management, were identified as more vulnerable. Additionally, both models were used to identify those stands, which would be most susceptible to damage by future windstorms. According to its explanatory power and building efficiency, we propose using of LRM rather than GAM in similar large-scale studies. The addressed methods can be used in local forest management, as scientifically based decision-making appears to be crucial for maintaining mountain forests resistant to gusty winds, as well as other disturbing agents.

Keywords: *driving factors; forest management; mountain spruce forests; wind disturbance; regression models, Slovakia*

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1. Introduction

In this study, we focused on forests of the central part of the Low Tatras in Slovakia, which were disturbed due to the windstorm Elisabeth in 2004. Besides the well-described role of ecological drivers on windstorm-driven deforestation in the near High Tatras, no similar research has been conducted in the Low Tatras. We used both logistic regression and generalised additive models to evaluate the impact of topographic and biotic factors in this area. Based on related research, the expected impact of topographic and biotic factors has been defined and summarised in the following hypothesis:

a. Trees on steep, convex slopes exposed to the prevailing wind direction during the disturbance in the vicinity of ridges are the most prone to windstorm-related damage;
b. Forest stands with homogenous species and age structure, with a high abundance of *Picea abies* and with higher trees of medium diameter are most prone to wind disturbances.

Apart from testing these hypotheses, we aim to:

a. Compare the performance of the LRM and the GAM using the receiver operating characteristics curve (ROC) and area under curve (AUC), as well as assess their suitability to evaluate and predict windstorm-driven damage;
b. Apply the final LRM and GAM that were trained on 2004 data to the current, up-to-date datasets, and thus, calculate an actual damage probability map.

2. Theoretical background

Temporary deforestation caused by extreme wind has always been an integral part of the forest disturbance regime and its circular restoration (Jakuš et al., 2015; Mezei et al., 2017a; White & Pickett, 1985). Despite windstorms not being a recent phenomenon, storm damage increased in Europe during the 20th century, mostly due to changes in forest management (Schelhaas et al., 2003). Moreover, wind events may reoccur more frequently in the current century due to climate change, which has the potential to invalidate historical baselines by altering the key drivers of disturbance regimes (Fleischer et al., 2017; Mezei et al., 2017b; Romagnoli et al., 2023). Besides other effects, wind damage to forests leads to carbon losses in the landscape (Seidl et al., 2014) and sometimes increases the risk of bark beetle outbreaks,

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particularly in dominant Norway spruce (*Picea abies* L. Karst) stands (Nikolov et al., 2014). At the same time, windstorms are the most serious, long-term, harmful agents in the forests, followed by bark beetles, whose increased population is also closely related to the consequences of wind disasters (Konôpka et al., 2016).

Evaluation of various environmental controls on the presence of temporary windstorm-driven deforestation is a frequently used and well-applicable approach to study the impact of windstorms on land cover changes in mountain areas. In addition to the models based on machine learning algorithms (Dobor et al., 2020; Schindler et al., 2016), a variety of regression models represent the most preferred methods of understanding the aforementioned impact. Among others, generalised linear models (GLM) (Hanewinkel et al., 2014; Kramer et al., 2001) and generalised additive models (GAM) (Falťan et al., 2009, 2020; Schmidt et al., 2010; Suvanto et al., 2019) pose the most effective and frequently used way to uncover relationships between windstorm-driven deforestation and its environmental drivers.

GLMs can simulate linear relationships between the response variable and explanatory variables. In the logistic regression models (LRM), the response variable is binary (Klaus et al., 2011). These models are easy to build and interpret (Suvanto et al., 2019). On the other hand, they cannot capture non-linear relationships. In order to understand non-linear patterns, the use of GAMs is recommended. GAMs estimate relationships between the dependent variable and predictors using a number of smoothing functions (Wood, 2017). However, GAMs are also highly prone to overfitting (Wood, 2008).

Regression models of forest damage are mainly stochastic, meaning their validity is regionally limited (Lanquaye-Opoku & Mitchell, 2005). This limitation is usually a consequence of the usage of low-coverage datasets and the area's microclimatic and topographic disparities.

The response variable entering the aforementioned models is connected to the extent of forest disturbance. Usually, this is described either spatially, as the presence/intensity of temporary deforestation in a coherent area (Kenderes et al., 2007; Krejci et al., 2018), or structurally, as tree mortality on selected field plots (Falťan et al., 2020; Seidl & Blennow, 2012). Elevation, slope, aspect, profile, planar curvature, slope position, and landforms have been assessed as the most relevant topographic explanatory variables in previous studies (Čada et al., 2016; Dobbertin, 2002; Kramer et al., 2001; Krejci et al., 2018; Mayer et al., 2005).

When taking into consideration biotic explanatory variables, the impact of these factors was often evaluated as follows: species structure of the stand (including the proportion of the coniferous species, mainly *Picea abies*), stand age, diameter at breast height (DBH), stand height, stand density, and the vicinity of the unforested (deforested) area (Jalkanen & Mattila, 2000; Klaus et al., 2011; Lohmander & Helles, 1987; Mikita et al., 2012; Ochtyra, 2020). Apart from topographic and biotic factors, soil (Falťan et al., 2020; Mayer et al., 2005) and anthropogenetic factors (Hanewinkel et al., 2014; Klaus et al., 2011; Klopcic et al., 2009) were investigated as well.

3. Data and methods

3.1 Study area

The Low Tatras is an extensive, west-east elongated mountain range situated in Central Slovakia. A major part of the mountain range is protected by the Low Tatras National Park.

The reference study area consists of two plots located south of the Low Tatras central ridge, namely Beňuška (plot A) and Babiná (plot B) (Fig. 1). Considering the specific behaviour of the wind masses in the rugged topography of this mountain range, only the most deforested southern part was selected for this study, specifically two south-directed side ridges and their surroundings. The choice of the plots was based on representativeness assessment, in the sense of spatial patterns of deforested areas, the presence of most typical landforms and the stand structure across the central part of Low Tatras. The size of each plot is approximately 2 × 4 km. There is a west-east distance of 6 km between the plots.

According to the Global Forest Watch data (Hansen et al., 2013), the tree cover of the reference study area was 79% in 2010. Predominant species in both bush and tree layers are *Picea abies*, *Fagus sylvatica*, *Acer pseudoplatanus*, *Abies alba*, *Sorbus aucuparia*, and *Pinus mugo*.

At some locations, species structure follows natural vertical zonality. Most of the landscape, however, was modified by intense logging and subsequent artificial forest restoration, which resulted in a high abundance of *Picea abies* monocultures.

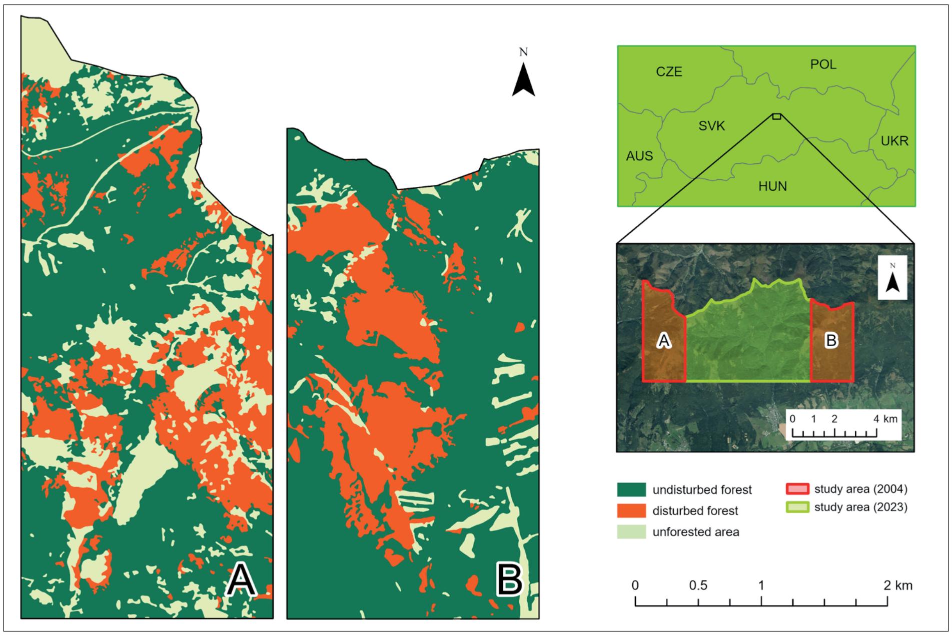

Fig. 1: Presence of deforestation after the Elisabeth windstorm (2004) in the study areas and its locations
Source: Ortophotomosaics of the Slovak republic (2021), provided by the Geodetic and Cartographic Institute Bratislava and the National Forestry Centre

On November 19th, 2004, the study area was hit by the Elisabeth windstorm. Wind from the northwest reached a speed of 230 kph (Falťan et al., 2021). Between the years 2004 and 2005, 153 hectares of forests were damaged in the study area (2004) based on the Global Forest Watch. Subsequently, dynamic deforestation continued, as a bark beetle outbreak and related logging occurred.

3.2 Data

Variables that reflect both forest damage and could influence the local wind impact by topographic or biotic conditions, were used in the analysis. All of these variables were obtained or derived from a digital elevation model and forestry databases.

The response variable (marked as "DIST04") was set as binary, thereby distinguishing between "disturbed forest" and "undisturbed forest" (Fig. 1). All the extensive areas of wind stem breakages and trees uprootings, as well as stands with the apparent decrease of tree cover due to windstorm were classified as "disturbed forest". Creating more categories based solely on aerial photography would have introduced more error (Kenderes et al., 2007). Unforested areas (e.g. meadows, rocks, roads with paved surfaces, etc.) were excluded from further analyses.

The impact of a single natural disturbance, the Elisabeth windstorm (2004), was thus inspected. The presence of temporary deforestation was identified manually, using ArcGIS PRO 3.0. Land cover change detection was based on comparing aerial photography from the years 2002 (pre-disturbance state) and 2006 (post-disturbance state), provided by Eurosense Ltd. The size of the smallest identified area (0.1 ha), the minimum size of change polygons (0.02 ha), as well as the classification of forested areas were set based on the modification of the CORINE Land Cover method for detailed identification of spatial landscape structure by Oťaheľ et al. (2017).

A set of explanatory variables entering models is introduced in Table 1. Topographic variables were obtained from the digital elevation model "DMR 3.5". This 10 m resolution open-source DEM completed in 2015, is provided by The Geodesy, Cartography and Cadastre Authority of the Slovak Republic. According to our previous experiment (Šagát & Rusinko, 2022), topographic variables calculated from the more detailed "DMR 5.0" showed lower explanatory power than variables obtained from the "DMR 3.5".

All the rasters of selected topographic variables were computed in ArcGIS PRO 3.0. ASP takes 8 values, indicating the main directions the slopes face. *NWDIR* was defined as the difference between the actual slope aspect and a 135° direction, and so it ranges from 0 to 180° (Falťan et al., 2020). Regarding *TPI* (Weis, 2001), original DEM cell values were recalculated as the mean of 500 × 500 neighbour cells. Consequently, *TPI* raster values were obtained as the difference between recalculated and original DEM. Additionally, values were rescaled to 0–100 range, where 0 corresponds to the valley bottom and 100 to the ridge. *TWI* (Kopecký & Čížková, 2010) was calculated using tangent slope and flow accumulation rasters.

Stand variables data were obtained from layers of basic forest management units and the related plans of forest management (PSL), which had been provided by the National Forest Centre. Plans with validity starting from the years 1999 and 2004 were used, to capture the state of vegetation before wind disturbance. Stands with a maximum age lower than 10 years and a height lower than 2 meters were excluded from further analyses. *EUAG* considers two values: even-aged forest (0) and uneven-aged forest (1). Also, *FMR* is binary – "forest under conservation" (0) and "forest under active management" (1). *DBH* was calculated as the weighted average value, taking into consideration the actual tree species proportions. In the case of overlapping descriptions for a single forest unit (frequent occurrence in forests with multiple age categories), *DENS* was used as the weighting parameter in the calculation of other variables.

In ArcGIS PRO 3.0, values of the aforementioned variables were extracted to the grid point layer with a fixed distance of 10 m. Consequently, a randomised selection of observations was performed. Fifteen thousand points were selected for each *DIST04* response state, with a minimum mutual distance set to 20 m. The resulting attribute table was used for further statistical analysis.

3.3 Logistic regression model

All observations were divided between training and testing in RStudio 2022.02.0, maintaining the ratio of 80 : 20. A generalised linear model was fitted using the *glm* function in the *stats* package. The family was defined as binomial, and function was set to logit link. All continuous predictors were subjected to a logarithm and square root transformation tests to account for non-linear relationships. Those that showed a lower AIC than models with untransformed variables were included in the final model.

Moreover, we inspected the presence of potential multicollinearity between the predictors (Dormann et al., 2013; Zuur et al., 2010). The *vif* function from the *car* package was used to compute the generalised variance inflation factors (GVIF) (Fox & Monette, 1992). *NWDIR*, *DECX* and *AGE* exceeded the threshold of 4, and were thus removed from the model. Also, these variables

Category	Model variable	Abbrev.	Type	Unit
Topographic	Elevation	*ELEV*	continuous	m a.s.l.
	Slope	*SLOPE*	continuous	°
	Aspect	*ASP*	categorical	-
	Exposure to NW winds	*NWDIR*	continuous	°
	Planar curvature	*PLAN*	continuous	10^{-2} z unit
	Profile curvature	*PROF*	continuous	10^{-2} z unit
	Topographic Position Index	*TPI*	continuous	-
	Topographic wetness index	*TWI*	continuous	-
Biotic	Number of tree species in the stand	*SPC*	continuous	-
	Even / uneven-aged stand	*EUAG*	categorical	-
	The proportion of Picea abies in the stand	*PICEA*	continuous	%
	The proportion of deciduous tree species in the stand	*DECX*	continuous	%
	Maximum age of the stand	*AGE*	continuous	years
	Maximum height of the stand	*HGHT*	continuous	m
	The average diameter of the trees in the stand	*DBH*	continuous	cm
	Average tree density	*DENS*	continuous	-
	Forest management regime	*FMR*	categorical	-

Tab. 1: Explanatory variables entering the generalised additive model
Source: authors' conceptualisation

weren't used to fit a generalised additive model (see section 2.4). *HGHT* and *DBH* slightly surpassed the threshold, but were kept in the model, considering their importance and mutual relationship causing the multicollinearity. Insignificantly performing variables ($p < 0.05$) were excluded from the final model as well.

As a consequence, the *predict* function from the *car* package was used to estimate values of a testing data frame using the fitted LRM. The prediction type was set to response. Finally, we computed the receiver operating characteristic curve (ROC) and the area under curve (AUC) to assess the model classification ability (Fawcett, 2006). The *roc* function in the *pROC* package was used. Additionally, the *varImp* function from the *caret* package was applied to assess the relative importance of the model variables.

3.4 Generalised additive model

Generalised additive model was built in order to inspect non-linear relationships between the response variable and the predictors. In a GAM, the aforementioned relationship is approximated by the means of non-linear smoothing functions (Pedersen et al., 2019).

The GAM was computed using the *mgcv* package and *gam* function. The method of restricted maximum likelihood (*REML*) was applied. The family object was defined as binomial. The number of basic functions computed for the specified basis type (*k* value) was selected separately for each variable, taking into consideration the representativeness of the underlying relationship, as well as the computational efficiency (Wood, 2017). The selected value was lower than k = 15, and lower than EDFs in all the cases.

Model validation was performed similarly, as described in section 2.3. However, the *predict.gam* function in the *mgcv* package was used to predict the *DIST04* values of the testing data frame.

3.5 Probability map of a windstorm-driven damage

For the computation of an up-to-date damage probability map (Pawlik et al., 2022; Suvanto et al., 2019), a larger study area was delimited (Fig. 1). The set of used explanatory variables was introduced in section 2.2. Areas not covered by the layer of basic forest management units were defined as unforested and ignored in further analysis. The plans of forest management with validity beginning in the years 2014 and 2019 were utilised to obtain up-to-date stand variables data. Observations with $AGE < 10$ and $HGHT < 2$ were excluded. Again, *DENS* was used as the weighting factor in the re-calculation of explanatory variables, when several descriptions for the same forest unit overlapped. The grid point layer was used to extract the values of the aforementioned variables with a fixed distance of 10 m between the observations.

Damage probability was estimated separately using the LRM and the GAM. For the LRM, the *predict* function in the *car* package was used, while in the case of the GAM, the *predict.gam* function in the *mgcv* package was applied. In both cases, predictions were set to the scale of response (0–1).

As a consequence, predicted response states were assigned to each grid point in ArcGIS PRO 3.0. From these, two rasters were computed, where every 10 m cell corresponds to a certain response state. Finally, cell values of damage probability were reclassified into 10 intervals based on percentiles, so that each category had an even number of observations.

4. Results

4.1 Drivers of a windstorm-related damage

Similar trends regarding the relationship between the environmental factors and the presence of windstorm-driven temporary deforestation were demonstrated by both the generalised additive model and the logistic regression. In the LRM, elevation, aspect, forest management category, tree diameter, and the proportion of Norway spruce were the most important variables. In contrast, the significance of the tree height, forest density, age diversity and the number of tree species was marginal.

Our models show that the probability of the disturbance increases with the elevation. According to the GAM, forests growing between 1,200 and 1,400 metres above sea level are the most susceptible. Gentle slopes are more prone to damage compared to the steeper ones. In the case of planar curvature, convex slopes appear to be more endangered. The profile curvature was insignificant in both models. Slopes that are immediately exposed to the wind during the disturbance are the most vulnerable. In our instance, a northwest wind harmed the forests growing on the north, northwest, and northeast exposed slopes. The impact of TPI shows that the damage probability rises with the distance from the valley bottom, with the exception of the immediate surroundings of the ridge. The higher vulnerability of the forest appears to be connected to dry soils (represented by lower TWI).

As for the stand variables, the probability of disturbance increases with the proportion of Norway spruce. Trees of a medium diameter (40 cm) and a height of 25 m are the most prone to damage. Forests of the opened canopy are more vulnerable. Moreover, susceptibility decreases with the number of tree species in the stand. Uneven-aged forests appear to be more susceptible. In addition, higher windstorm-driven damage is expected in forests under active forestry management, when compared to the protected ones.

Effect plots of selected predictors are shown in Figure 2 and Figure 3.

4.2 Model comparison and application

The logistic regression model showed $AUC = 0.80$ on both training and testing data frame. The generalised additive model reached the $AUC = 0.85$ on training data and $AUC = 0.84$ on testing data. As a rule of thumb, these values are generally regarded as acceptable. Also, the GAM scored $R^2 = 0.38$. Windstorm-driven damage probability maps (Fig. 4) show how input variables synergically affect the risk of a future damage.

5. Discussion

5.1 Comparison of the logistic regression model and the generalised additive model

According to the values of AUC on both training and testing datasets, the GAM did not perform markedly better compared to the LRM. Nevertheless, it was helpful in understanding the non-linear relationships between the presence of disturbance and some predictors, especially elevation, TPI, and the DBH. Falťan et al. (2020) states the advantages of GAM in interpreting the influence of soil factors on wind disturbances, which were not the focus of our study. Based on the correct classification score, the efficiency of using the GAM remains questionable. It is more time-consuming to construct and more complicated to interpret than the LRM (Suvanto et al., 2019). Moreover, reliability of its results can be easily compromised by overfitting and by the usage of an inadequate number of basic functions computed for the specified basis type (Wood, 2017).

5.2 The impact of abiotic drivers on windstorm-driven deforestation

In this case study, both the GAM and LRM showed a positive dependence between values of elevation and damage probability. The same relationship was described by Klaus et al. (2011) and Mikita et al. (2012). Contradictory results were published, e.g. by

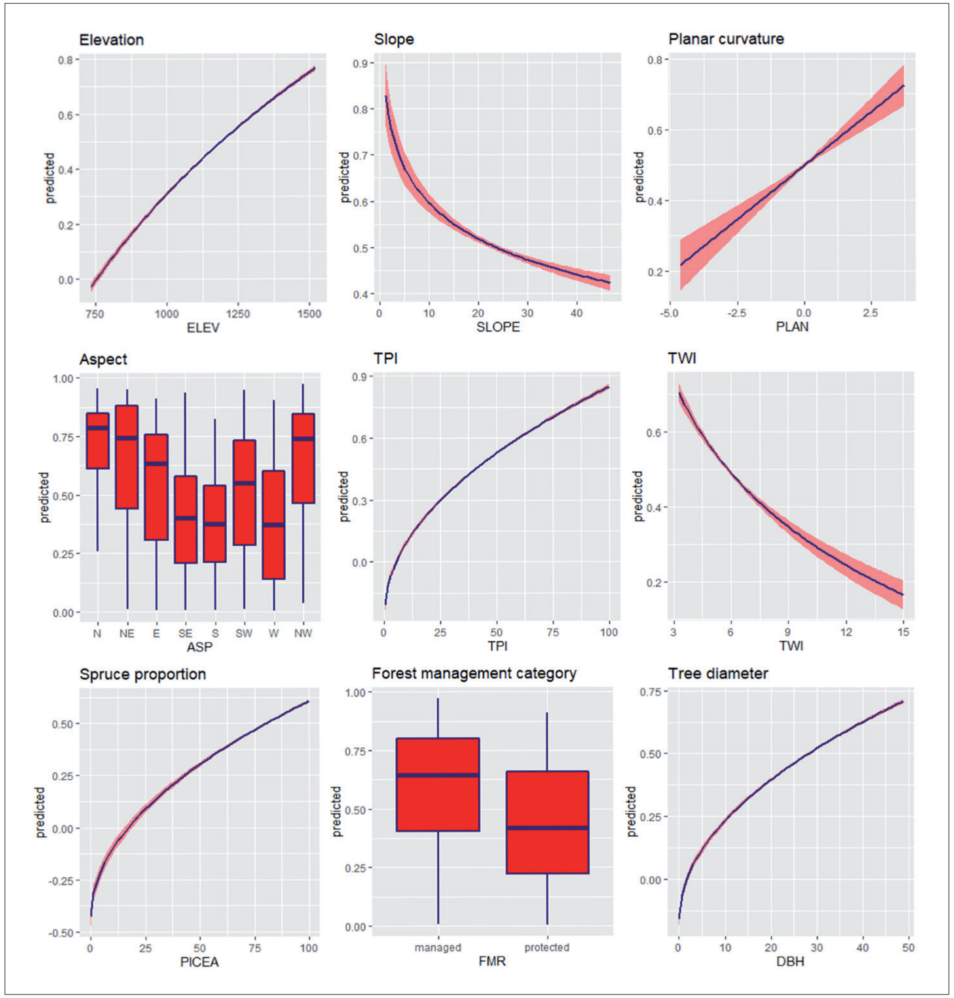

Fig. 2: Logistic regression partial effect plots of the explanatory variables. X axis describes data distribution. Y describes damage probability estimated by the fitted LRM on the test data frame. 95% confidence interval used (red). Only the most important predictors are displayed based on varImp values. TPI- Topographic Position Index; TWI- Topography Wetness Index.
Source: authors' calculations

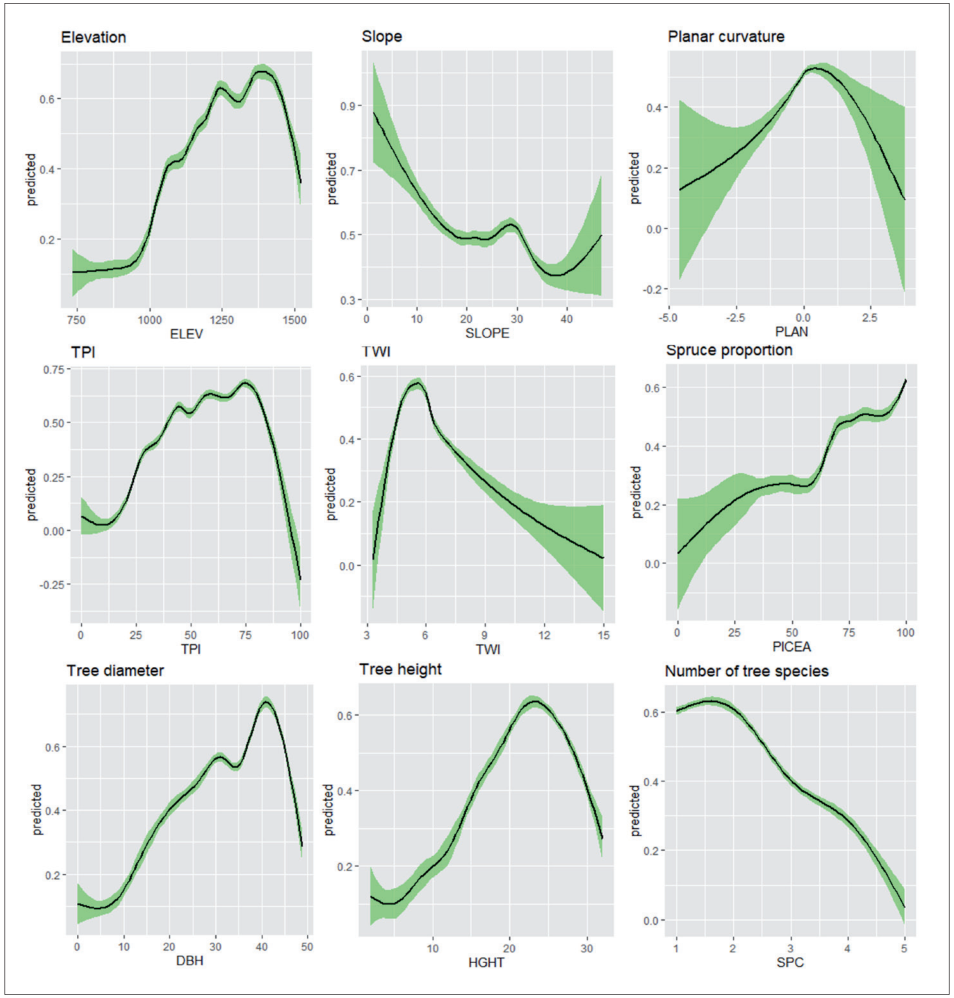

Fig. 3: Generalised additive model partial effect plots of the explanatory variables. X axis describes data distribution. Y describes damage probability estimated by the fitted GAM on the test data frame. 95% confidence interval used (green). All model variables are displayed, except for factor and tree density. TPI- Topographic Position Index; TWI- Topography Wetness Index
Source: authors' calculations

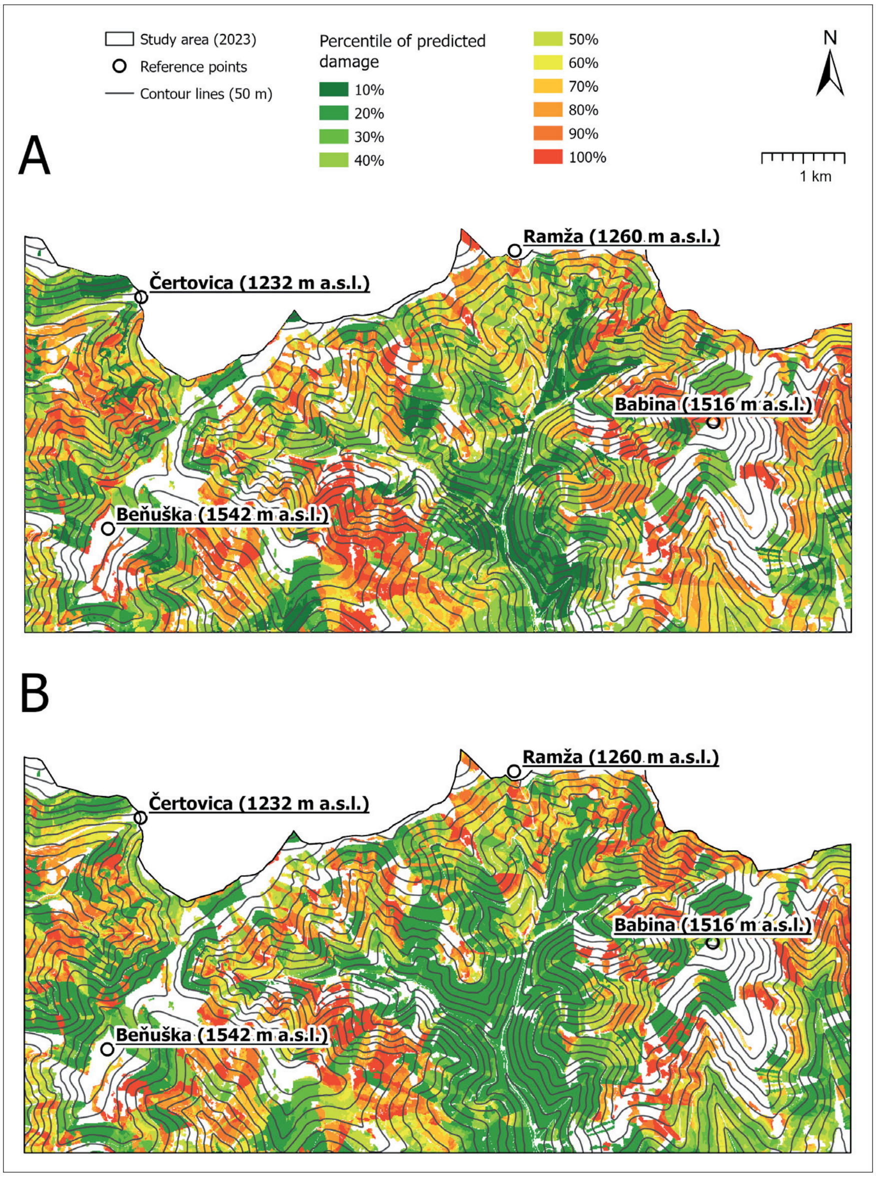

Fig. 4: Windstorm-driven damage probability maps based on the logistic regression model (A) and the generalised additive model (B)
Source: authors' calculations and elaboration

Minár et al. (2009), while others found this variable insignificant (Dobbertin, 2002; Schmoeckel & Kottmeier, 2008). It must be pointed out that elevation is a proxy variable, reflecting another abiotic control, for instance, higher wind speed (Svoboda et al., 2012). The character of the windstorm, however, as well as the topographic disposition of the study area, must be taken into consideration when interpreting the impact of elevation on deforestation. For example, in the High Tatras, windstorm Elisabeth affected mostly the colluvial slopes with lower elevation, where it took a form of bora — a warm mass of air falling from the High Tatra peaks directly to the basin with embracing speed (Falťan et al., 2009).

According to our models, gentle slopes are more prone to windstorm-driven damage compared to steep ones. Mayer et al. (2005) explain this as a consequence of more intense water logging compared to the steep slopes with a higher runoff, and thus worse soil conditions to fix a root system.

In our case, gentle angles were connected prominently to the ridge's surroundings and initial slopes. Therefore, this relationship can be explained by the aforementioned higher wind speed near the ridges rather than more intense water logging. Different outcomes were reported by Dobbertin (2002) and Ochtyra (2020), who consider moderate slopes to be the most prone to damage. Larger study areas were inspected, however. Moreover, we tested a tangent slope angle as an alternative variable, but it did not perform significantly, meaning the slope does not affect the presence of deforestation via gravity forces (Falťan et al., 2020).

Considering slope position, some authors (Čada et al., 2016; Klopcic et al., 2009; Schütz et al., 2006) agree that the risk of deforestation increases from the valley bottom to the ridges. Our findings mostly support this premise. As uncovered by GAM, however, the probability of the disturbance rapidly decreases in the ridge's surroundings. This can be explained by the high abundance of unforested areas in the close ridge's surroundings. According to Stathers et al. (1994), this relationship is more complex and depends on the prevailing wind direction. Kramer et al. (2001) point out that valley bottoms can be endangered as well due to the so-called "valley effect", which includes channelling and bending of the wind.

Slope curvature is a rarely studied explanatory variable (Falťan et al., 2020). In our study, convex slopes were more susceptible to damage compared to concave ones, especially in terms of planar curvature, which correlates to the findings of Hanewinkel et al. (2014). Profile curvature did not perform significantly.

Our models indicated that the most vulnerable to the windstorm-driven deforestation in the study area are the north, northeast, and northwest facing slopes, which were directly exposed to the northwest wind during the disturbance. Similar results were published by Dobbertin (2002). The "Lee slope effect" described by Everham and Brokaw (1996) and Foster and Boose (1992) was not observed. Aspect entered the models as a factor variable. We also tested two numeric modifications: extra variable *NWDIR*, which reflects slope exposition to the prevailing wind direction, and alternative calculation of ASP as northness and eastness (Roberts, 1986). While the former was removed from the model due to multicollinearity, the latter was insignificant in both models.

TWI is another marginally-used variable (Pawlik et al., 2022). In the study area, wet positions are not sufficiently represented due to the rugged relief with the steep slopes. As the GAM shows, very dry positions tend to be less susceptible to windstorm damage when compared to moderately dry ones.

As for abiotic variables, some authors tend to use edaphic variables in their models as well (Mayer et al., 2005; Panferov et al., 2009; Ruel, 2000). In our study area, soil characteristics were mapped only on medium and small scales. Therefore, they could not be implemented in our model, especially when considering the size of the study area.

5.3 The impact of biotic drivers on windstorm-driven deforestation

The higher number of tree species in the stand positively affected forest resistibility to damage. This has a close connection to another observed relationship – a rising risk of damage with a rising proportion of Picea abies. As mentioned previously in section 2.1, the natural species composition of the Low Tatras forests has been modified by the planting of spruce monocultures. There is a general consensus on that when it comes to windstorm-driven damage; coniferous stands are more endangered than deciduous ones (Albrecht et al., 2012; Lohmander & Helles, 1987; Ruel, 1995; Usbeck et al., 2010). In comparison with the deciduous tree species, spruce has both a superficial rooting prone to rotting, as well as a disproportional ratio between the tree height and the DBH (Klaus et al., 2011). Also, heterogenous stands positively affect soil productivity, as the humification and mineralisation of organic remains originating from different tree species maintain different speeds. Moreover, outside the growing season, evergreen species have a higher wind load, in contrast to leafless deciduous trees (Dobbertin, 2002). According to Krejci et al. (2018) and Valinger and Fridman (2011), even 25–30% of deciduous species in the stand can reduce the risk of damage by 50%. Despite these facts, semi-extensive planting of Norway spruce is an ongoing process in Slovakia due to economic interests (fast growing, high heat value, variety of applications).

Klopcic et al. (2009) point out that even-aged forests were more prone to windstorm-driven damage than heterogenous ones. Despite our findings being different, this can be explained by the forestry datasets used, where both shrubs and mature forests were frequently included in a single stand unit. Such heterogenous vertical structure can signify affect both opened canopy and the high abundance of forest edges, which enhance stand susceptibility (Mikita et al., 2012). The variable AGE has to be removed from our models due to multicollinearity, but the results of Jalkanen and Mattila (2000) and Ochtyra (2020) indicate that higher stand age increases the risk of deforestation. This can be reasoned by higher susceptibility to parasite attacks and diseases in the case of old trees, as well as longer development of tree height compared to the development of root depth (Lohmander & Helles, 1987).

When considering forest density, stands with an opened canopy tend to be more susceptible according to our models. The influence of this variable was marginal, however, which is in line with the findings of Hanewinkel et al. (2014) and Mikita et al. (2012). Kenderes et al. (2007) point out that the stands with a closed canopy can also be endangered due to thinning. Insufficient light conditions result in a competitive behaviour of individual trees, which relates to the high stems with low DBH. This phenomenon is more prevalent in monocultures.

As presented by Everham and Brokaw (1996), Klopic et al. (2009), and Peterson and Pickett (1991), trees of medium diameter (approximately 30–50 cm) are the most prone to windstorm-driven damage. This can be explained by both the shelter of the smallest trees and the resilience of the largest ones. The described dependence is in line with the relationship uncovered by our GAM.

DBH has a close bond to another frequently studied variable – tree height. Some authors (Schütz et al., 2006; Valinger & Fridman, 2011) use a ratio between the DBH and the tree height as a single predictor. As shown in Figure 3, these two variables are characterised by similar patterns of its influence on the damage severity, with medium-high trees (20–30 m) being the most susceptible. The importance of the DBH was more prominent compared to the tree height in the LRM, however. Nevertheless, this relationship is strongly influenced by other stand variables, e.g. forest density, which can determine the aforementioned thinning (Lohmander & Helles, 1987).

5.4 Forest management implications

Forest management interventions essentially modify the vertical and horizontal structure of the forest, as well as its species composition. Through these predictors, the susceptibility of forests to natural disturbances is determined. According to the LRM, protected forests and special-objective forests are more resilient to damage, when compared to those under active management, although the difference in damage probability is not substantial.

As implied in section 4.2, maintaining diverse forests in the sense of species composition and age structure is essential for its future stability and resilience against natural disturbances. In the natural reservations and the cores of protected areas, a non-intervention approach is recommended, as the natural forest development, which includes both disturbances and the stand restoration, is sufficient for creating a heterogenous structure (Nováková & Edwards-Jonášová, 2015).

Besides the protected areas, a non-intervention scheme is not suitable, as the windbreaks and windthrows quickly turn into hotspots of subcortical insect infestations (Sproull et al., 2015). Therefore, the application of small-scale, irregular shelterwood and single-tree selection systems is suggested to increase the heterogeneity of the stand artificially (Klopcic et al., 2009). It must be noted that the high proportion of medium-scale cuts increases the density of susceptible forest edges (Lohmander & Helles, 1987).

According to Griess et al. (2012), intentional mixing of tree species in a single stand enhances its resilience to the natural disturbances. Additionally, it is crucial to reduce the proportion of Norway spruce in the areas outside its natural distribution, as the species vitality and defence mechanisms are failing under ongoing climate change (Dobor et al., 2020; Šagát et al., 2021).

6. Conclusion

In this case study, we constructed both a logistic regression model and a generalised additive model to better understand the factors that contributed to deforestation in the Central Low Tatras of Slovakia following the Elisabeth windstorm in 2004.

Both hypotheses, describing the expected influence of the selected topographic and biotic variables on the presence of deforestation, were verified. When considering topography, the most prone to windstorm-driven damage are forests on steep convex slopes exposed to the disturbance's dominant wind direction, especially in the vicinity of ridges. Regarding the stand characteristics, medium tree diameter and the high proportion of Norway spruce are the leading determinants of deforestation. While tree height and species structure displayed the expected effects, their importance was unsubstantial and stand age did not perform significantly.

As indicated by AUC values, the generalised additive model did not significantly outperform the logistic regression model, which is also more efficient to build and easier to interpret. Additionally, windstorm damage probability maps were computed, enabling the identification of the most endangered stands across the study area and the adjustment of management interventions to lower the risk of future extensive disturbances.

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