Environmental risk assessment based on semi-quantitative analysis of forest management data

L. Kulla[1], R. Marušák[2]

[1]*Forest Research Institute in Zvolen, National Forest Centre, Zvolen, Slovakia*

[2]*Faculty of Forestry and Wood Sciences, Czech University of Life Sciences Prague, Prague, Czech Republic*

ABSTRACT: The paper deals with environmental risk assessment in prevailingly unnatural spruce (*Picea abies* [L.] Karst.) forests in three regions with different patterns of forest damage in the Slovak part of the West Carpathians. Logistic regression was used to estimate the effect of 7 site-related, 5 stand-related and 2 anthropogenic factors on the probability that critical forest damage will occur. The results show that regression models can describe cause-effect relationships in regions with different regimes of forest decline. Stand age, proportion of spruce, and distance from the focus of biotic agent activity predicted decline in two regions with generally lower elevation in northern Slovakia (Kysuce and Orava). In a mountain region (Low Tatras), the importance of factors contributing to the static stability of trees and position towards dangerous winds increased significantly. The quality of the derived models and prospects for their usefulness in risk assessment are discussed.

Keywords: ecological factors; forest damage; forest management; logistic regression; Norway spruce; risk assessment

The general forest management scheme in Europe primarily aims to achieve high-quality and large-dimension timber production, which, depending on site conditions and tree species growth characteristics, usually requires a growing period of about 100 years or longer. A wide range of disturbances typically occurs during this period. Because a profit is expected at the end of the forest production cycle (rotation period), each aspect or incidence of damage causes a loss in value. Therefore one of the main tasks of forest management is to reduce such damage by the proper long-term planning of suitable silvicultural measures.

Risk is defined in terms of a loss event (disturbance) that is comprised of two components: potency (cost, severity, or extent of the loss event) and chance (the likelihood of occurrence the loss event). Sometimes only potency is examined, and this is measured in terms of severity, intensity or level of mortality. It is often referred to as “hazard”. In other instances, risk is analyzed only as the likelihood of a loss event, wherein either probability of an event is estimated or predisposition to a loss event is assessed (Schmoldt 2001).

Modelling of tree mortality as a highly stochastic process is limited. Therefore, Hawkes (2000) suggested a shift towards modelling for purposes of exploration and explanation rather than for the aim of generating precise predictions.

Several approaches to risk assessment in forest management were described by Hanewinkel (2002). The first approach is based on an extensive literature review or even just on local experience. Its examples are expert systems used in assessing the influence of site and stand factors on the bark beetle hazard in spruce stands (Jakuš 1998; Nopp et al. 2001), a system for the honey fungus risk assessment under climate change (Čermák et al. 2004) or a simple qualitative risk rating scheme for main European tree species and main types of risk (Bredemeier et al. 2001). The second approach – actually the most common – is the use of various

Supported by EU through the ERDF-funded operational programme of Slovak Republic "Research and Development", Project No. ITMS26220220026, and by the Ministry of Agriculture of the Czech Republic, Project No. QH91097.

deterministic and stochastic models. An example of the deterministic approach is to derive transition probabilities for age classes using Markov chains (Suzuki 1971). Such a technique was applied to estimate the influence of salvage cuttings on harvesting strategies (Kouba 1989) and on insurance models in forestry (Holécy, Hanewinkel 2006). Logistic regression is a frequently used stochastic technique for risk assessment in forestry – for example for the analysis of wind and snow damage (Valinger, Fridman 1999; Jalkanen, Manttila 2000) or for the occurrence of general forest damage (Kulla, Hlásny 2008). A third alternative is the use of artificial intelligence techniques – for example artificial neural networks to build nonlinear regression models (Schmoldt 2001; Hanewinkel 2002).

This paper presents the results of a logistic regression-based risk analysis utilizing forest management data. The analysis was carried out in unnatural Norway spruce forests affected by different types of forest decline. The findings can provide effective support to optimization of medium- and long-term forest management planning. In particular, we focus upon:

(1) introducing the data and methodology used in the analysis,
(2) developing and describing logistic regression models for three spruce-dominated regions in the West Carpathians,
(3) discussing the prospects of such models to be used in forest management.

MATERIAL AND METHODS

Regions of interest

Three spruce-dominated regions in the Slovak part of the West Carpathians, representing various site conditions and disturbance regimes, were subjected to analysis (Fig. 1). Intensive spruce decline has been observed in all three regions in recent years.

The Kysuce region represents a lower situated hilly landscape. The geological substratum is palaeogenetic flysch, built of sandstone, slate and claystone. Moderately cold and very wet climate is typical of the region. Recently, bark beetles (*Scolytidae*) and honey fungus (*Armillaria* sp.) have played the most important roles in spruce decline in this region (Fig. 2).

The Orava region also belongs to the West Beskids flysch geological sub-base. Its geomorphology is much more diverse compared to the Kysuce region, with hilly and high mountain parts. Cold and very wet climate prevails. Recently, elevated activity and severity of both destructive (mainly wind and snow) and biotic damage have been observed.

The Low Tatras region represents a typical Central Carpathians high-mountain massif built of crystalline silicate rocks. The climate is cold and wet, but more continental than in the previously named regions. Long-term impacts of windstorms with subsequent bark beetle outbreaks comprise a typical forest disturbance regime.

Description of variables

Data from forest management plans in use at the beginning of the 10-year period of interest were used for analyses. Seven site-related, five stand-related, and two anthropogenic factors with the assumed influence on the probability of forest damage occurrence were used as explanatory variables in the logistic regression models (Table 1). All of them were either directly available in forest management plans or were derived from these data.

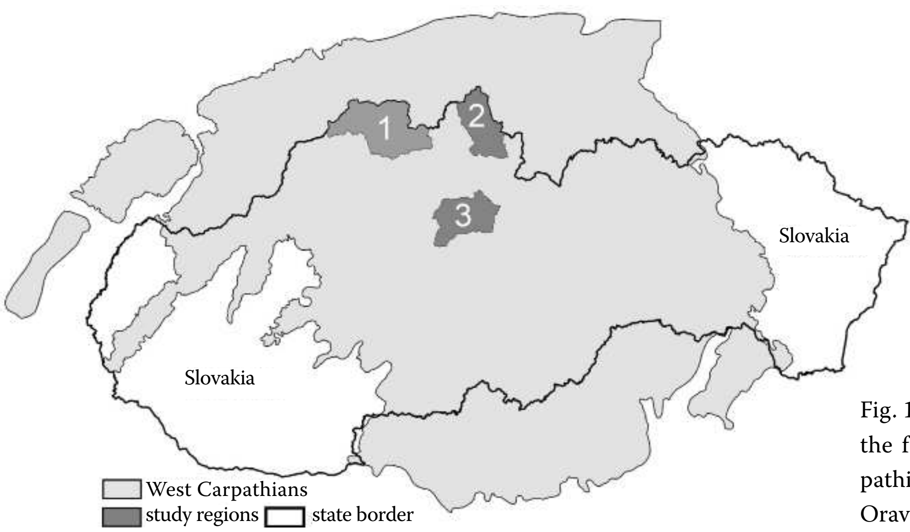

Fig. 1. Localization of study regions in the frame of Slovakia and West Carpathians. 1 – the Kysuce region, 2 – the Orava region, 3 – the Low Tatras region

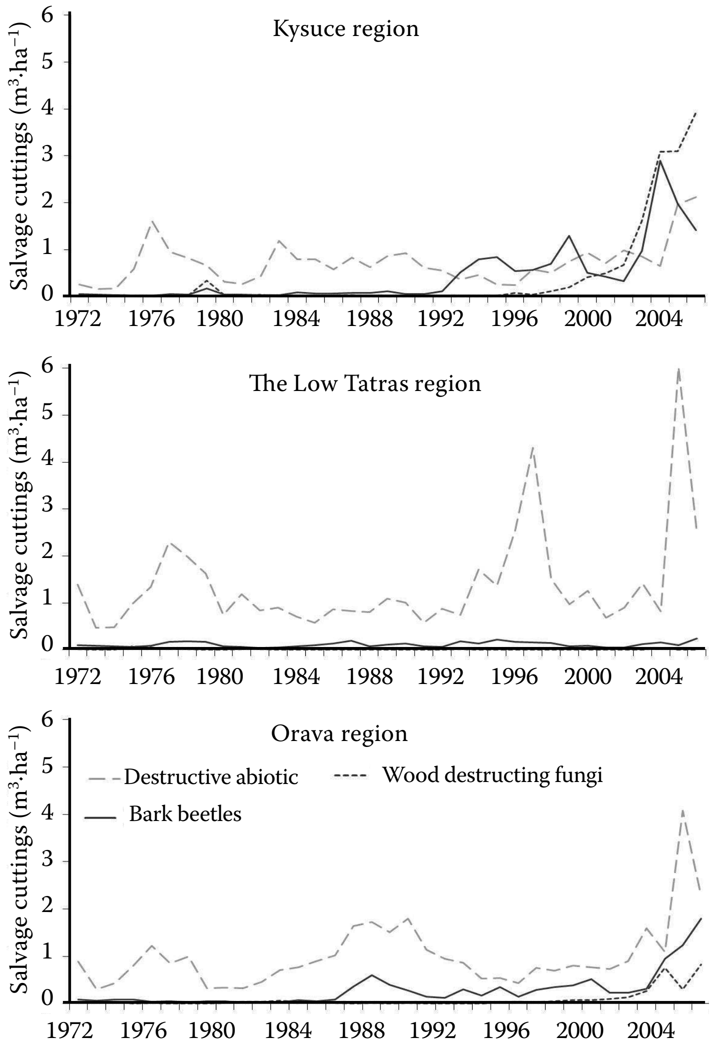

Fig. 2. Differences between the importance of biotic and abiotic destructive agents in the study regions

Qualitative variables were quantified by means of simplified ordinal scales (for details see Table 1).

The dependent variable was designed on the basis of direct visual assessment of forest damage according to classification scales given in Table 2. Critical damage occurrence (level 3) expressed on a binomial scale (1 – critical damage occurred; 0 – critical damage did not occur) was ultimately used as the dependent variable. Such assessment was carried out on sample plots arranged on linear transects situated across the Kysuce and Orava regions in directions of the highest variability of site and stand conditions.

Sample plots approximately 1 ha in size and representative of the surrounding forest stand were identified in each forest compartment through which a transect line passed. Airborne imagery taken in the period prior to the occurrence of extensive spruce dieback (2002–2003) was used for pre-selection of sample plot centres. Plot centres were visually pre-selected, considering the relief, tree species composition and canopy structure. Subsequently, plot centres were identified in the field by GPS. In this way, 297 sample plots were designed in the Kysuce region and 245 in the Orava region during the period 2007–2008.

No field survey was carried out in the Low Tatras region. A linear discriminant model was designed using the Orava dataset to obtain a dependent variable for the Low Tatras region (Table 3). Two out of the five tested discriminators were included in the final model using a stepwise forward procedure: stand age and proportion of salvage cutting in actual timber stock. Subsequently, using available data from forest management plans and records of salvage cutting, scores for critical damage occurrence were assigned to all forest compartments in this region. Discriminant model parameters (Table 3) indicate the significance of discriminant functions, which was proved by a test of Mahalanobis distance. The model was also proved to have fairly good stability by its validation on an independent data set from the Kysuce region, although the accuracy of classification was only about 80%.

Table 1. Explanatory variables used for the development of logistic regression models and scales used for quantification of individual variables

Factor		Scale		
		type	range	
Site	altitudinal vegetation zone	ordinal	3–6	3: oak-beech … 6: fir-beech-spruce[1]
	ecological-trophical order	ordinal	1–6	1: oligotrophic … 6: calcaric[1]
	hydric order	ordinal	1–5	1: extremely limited … 5: waterlogged[1]
	site extremity	ordinal	1–3	1: no extremity … 3: high extremity[1]
	natural presence of beech	binomic	0–1	0: natural absence … 1: nat. presence[1]
	radiation load	ordinal	1–4	1: N-NE expositions … 4: SW-S exp. [2]
	zone of biotic hazard	ordinal	1–3	1: no hazard … 3: focus of activity[3]
Stand	stand age	cardinal		years
	proportion of spruce	cardinal		% of relative crown cover
	stand density	ordinal	1–10	1: crown cover 5–15% ... 10: 95–100%
	vertical structure	ordinal	1–3	1: one layer … 3: three or more layers
	initial damage	ordinal	1–3	1: undamaged … 3: critically damaged[4]
Man	pollution load	ordinal	0–2	0: without load … 2: medium load[5]
	management system	ordinal	1–3	1: reliable … 3: questionable[6]

[1]Ecological factors derived from the qualitative parameter "forest type" according to Hančinský (1972), quantified according to Zlatník (1976) and Buček and Lacina (2000)

[2]relative radiation input, assessed by relief aspect

[3]biotic hazard categories designed as result of spatial analysis of sanitary cuttings caused by biotic agents (for details see Kulla, Hlásny 2008; Hlásny et al. 2009)

[4]forest damage at the beginning of the model parameterisation period scaled according to Table 2

[5]assessed level of both present-day and past air pollution load, spatially expressed by "zones of pollution threat" according to forest management legislation in Slovakia

[6]the reliability of systematic management is prejudged by a decreasing gradient, starting from state forests, through municipality and community forests, to small owners' forests, often without legal personality

Methods

Logistic regression can be used to predict a dependent variable on the basis of continuous and/or categorical independents. Logistic regression applies maximum likelihood estimation after transforming the dependent into a logit variable (the natural log of the odds of the dependent variable occurring or not). In this way, logistic regression estimates the probability of occurrence of a certain event (e.g. DeMaris 1992).

Logistic regression was used to identify the influence of cardinal, ordinal and binomial explanatory variables (Table 1) on critical forest damage occurrence. Deviance residuals and Pearson χ^2 residuals were calculated to check the suitability of the designed model for the prediction. Deviance residuals are based on the contribution of the observed responses to the log-likelihood statistic, while Pearson χ^2 is expressed as the difference between the observed responses and predicted values.

A logistic regression model was created using the GLM module in STATISTICA 7.0. The logit link function and the forward stepwise procedure for factors entering the model were applied. The results were interpreted according to standard procedures used for the evaluation of logistic regression models (e.g. Meloun et al. 2005).

RESULTS

The quality of the derived models as indicated by the ratios of residuals and degrees of freedom was satisfactory. The ratios were below or close to 1.0 in all cases (Table 4), and thus there was no evidence of overdispersion and the models fitted the data well (Hosmer, Lemeshow 2000). In addition, how well the regression models fitted was assessed by the proportion of cases correctly classified by the model and observed values of the dependent variable. While overall correctness of all models varied in a range of 82–93%, in

Table 2. Forest damage classification and assignment of binary values to "critical damage occurrence" in order to create a binomial dependent variable for logistic risk regression model

Damage level	Critical damage occurrence	Canopy compactness	Canopy transparency
1 – undamaged	0	intact	< 30%
2 – moderately damaged	0	disrupted (gaps < 0.01 ha prevail)	30–60%
3 – critically damaged	1	open (patches > 0.01 ha prevail)	> 60%

less frequent category 1 (critical damage occurred) the classification was much poorer and varied between 38% and 73%, depending on the proportion of this category in model calibration data (Table 5).

No over- or underestimation was detected in the Orava region, where the ratio of risk category 1 to category 0 was nearly 1:2. Underestimation by about 13% was detected for category 1 in the Kysuce region, where this ratio was nearly 1:3. This indicates that the number of forest compartments with predicted critical forest damage was lower by 13% than the number of compartments with observed critical damage. In the Low Tatras region, this value approached 1:10 and an underestimation of 47% was detected for risk category 1. Hence, these results should be regarded as less reliable and to have reduced applicability as compared to those from the previous regions. In addition, the indirect assessment of critical damage using a discriminant model markedly limits the use of the acquired results.

Table 4 describes differences in the cause-effect pattern among the studied regions. In the Kysuce region, which has been massively affected mainly by biotic agents in the last decade, the highest probability of critical damage occurrence was associated with older stands, higher proportion of spruce, location in the vicinity of the focus of biotic agent activity, and growing at drier sites (the order is based on Wald statistics).

Mature stands at lower altitudes, northern exposures, and at the wettest sites were found to be the most endangered in the Low Tatras region. Supposed reasons are the susceptibility of stands to windthrow due to larger dimensions of trees, lower rooting stability, and exposure to prevailing wind directions (according to Konôpka et al. 2008). The position towards the focus of biotic pest activity also plays a role as do the increasing proportion of spruce, higher level of initial damage, and management uncertainty (for variable descriptions see Table 1). This probably relates to the frequent neglect of tending and forest sanitation measures on the part of small owners.

In the Orava region, where the disturbance pattern is in transition between the previous regions, the order of factors was similar to that for the Kysuce region. The most important factors were the position towards the focus of biotic pest activity, stand age, and the proportion of spruce in a given stand. The fourth

Table 3. Linear discriminant coefficients and parameters of the discriminant model, used for the estimation, whether the critical damage occurred or did not occur in the Low Tatras region, as a surrogate of direct visual classification of forest damage

Factors tested as potential discriminants	Risk category	
	0 (critical damage did not occur)	1 (critical damage occurred)
Stand age	+0.106	+0.133
Salvage cuttings proportion[1]	–0.011	+0.099
Stand density	0	0
Vertical structure	0	0
Initial damage	0	0
Interception	–3.844	–8.065
Mahalanobis distance test		$M^2 = 2.84$; $F = 74.1$; $P = 0.00$
Corectness of classification on analyzed data (Orava region, $n = 226$)		78.3%
Corectness of classification on independent data (Kysuce region, $n = 286$)		85.7%

[1]% of removed timber stock in the forest compartment since the beginning of the analyzed period due to a salvage cuttings, M^2 – Mahalanobis distance, F – F-test value, P – F-test signification

Table 4. Results of logistic regression, evaluating estimated influence of searched factors to the critical damage occurrence in all study regions. Signs of b_i indicate whether increasing value of factors (according to scale in Table 1) influence critical damage occurrence positively or negatively, increasing values of Wald statistic indicate the statistical weight of this influence. Empty fields means that factor was not included to the model by forward stepwise procedure

Explanatory variable (b_i)	Kysuce region		Orava region		The Low Tatras region	
	estimation	Wald st.	estimation	Wald st.	estimation	Wald st.
	b_i	$(b_i/s(b_i))^2$	b_i	$(b_i/s(b_i))^2$	b_i	$(b_i/s(b_i))^2$
Altitudinal vegetation zone	–	–	–	–	–1.231	148.2**
Ecological-trophical order	+0.837	4.2*	–	–	–	–
Hydric order	–1.757	14.1**	–	–	+0.412	15.3**
Site extremity	–	–	–	–	–	–
Natural presence of beech	–	–	–	–	–	–
Radiation load	–	–	–	–	–0.268	18.2**
Zone of biotic hazard	+1.611	22.0**	+1.711	21.9**	+0.641	24.0**
Stand age	+0.076	35.5**	+0.042	16.6**	+0.077	414.4**
Proportion of spruce	+0.091	34.2**	+0.079	13.7**	+0.010	13.9**
Stand density	–	–	–	–	–	–
Vertical structure	+1.174	6.5*	–2.391	11.7**	–	–
Initial damage	–	–	+0.959	6.2*	+0.335	8.1**
Pollution load	–	–	+1.323	6.3*	–	–
Management system	–	–	–0.630	3.6*	+0.366	7.2**
Intercept	–16.41	38.8**	–15.49	27.7**	–5.94	74.7**
Deviance (D/df)	0.55		0.72		0.37	
Pearson residuals (χ^2/df)	0.57		0.67		0.67	

**$P < 0.01$; *$0.01 < P < 0.05$, Wald st. – Wald statistic, s – standard deviation, D – deviation of the model, df – degree of freedom, χ^2 – chi squared distribution

factor was the vertical stand structure which indicates increasing importance of destructive damage.

DISCUSSION

The developed regression models can be considered as standalone complex models of environmental risk prediction allowing the "chance and potency" analysis using a traditional regression technique (Schmoldt 2001). "Chance" is computed as probability of the critical damage occurrence for forest compartments and "potency" is a specific level of forest damage considered as critical in forest management.

The results proved the statement of Hanewinkel (2002) that the ability of such models to predict damage to forest is limited, especially when the numbers of damaged and undamaged stands in the sample data differ significantly. The results indicate a possibility of under- or overestimation of predicted risk given unbalanced data sets, i.e. when one risk category prevails over another at a ratio lower than 1:3.

Table 5. Classification matrices expressing the correctness of classification of cases (sample plots, in the case of the Low Tatras region forest compartments) from the analysed data set by derived logistic models

Kysuce region				Orava region				The Low Tatras region			
Observed	predicted			observed	predicted			observed	predicted		
	1	0	correct (%)		1	0	correct (%)		1	0	correct (%)
1	47	23	67.1	1	58	22	72.5	1	152	252	37.6
0	14	213	93.8	0	23	142	86.1	0	63	3,960	98.4
All			87.5				81.6				92.9

Hence, an adjusting procedure can be performed on logistic regression results, e.g. shifting the threshold point of the relative operational characteristic (Meloun et al. 2005) or using alternative techniques such as those based on artificial intelligence.

The developed regression models identified understandable and ecologically well interpretable region-specific cause-effect interactions. As the models have been developed using data from forest management plans, quantitative information about risk (probability of critical damage occurrence, including confidence intervals) associated with individual forest compartments can be obtained. In this way, the results can provide profound information for knowledge-based forest management. While recognizing the aforementioned limitations, the proposed system based on the quantification of qualitative forest management data appears to be suitable for complex environmental risk assessment using generally available data.

References

Bredemeier M., Lamersdorf N., Schulte-Bisping H., Lupke B.V. (2001): Risk appraisal for forest management with respect to site quality and environmental changes. In: Gadow K.V. (ed.): Managing Forest Ecosystems 2: Risk Analysis in Forest Management. Dordrecht/Boston/London, Kluwer Academic Publishers: 21–48.

Buček A., Lacina J. (2000): Geobiocenology II. Brno, MZLU: 249. (in Czech)

Čermák P., Jankovský L., Cudlín P. (2004): Risk evaluation of the climatic change impact on secondary Norway spruce stands as exemplified by the Křtiny training forest enterprise. Journal of Forest Science ***50***: 256–262.

DeMaris A. (1992): Logit modeling: Practical applications. Thousand Oaks, CA: Sage Publications. Series: Quantitative Applications in the Social Sciences, ***106***: 87.

Hančinský L. (1972): Forest Types of Slovakia. Bratislava, Príroda: 307. (in Slovak)

Hanewinkel M. (2002): Climatic Hazards and their Consequences for Forest Management. In: Arbez M., Birot Y., Carnus J.M. (eds): Risk Management and Sustainable Forestry. EFI Proceedings, ***45***: 21–28.

Hawkes C. (2000): Woody plant mortality algorithms: description, problems and progress. Ecological Modelling, ***126***: 225–248.

Hlásny T., Kulla L., Barka I., Turčáni M., Sitková Z., Koreň M. (2009): The proposal of biotic hazard zones in selected spruce dominated regions in Slovakia. Journal of Forest Science ***56***: 236–242.

Holécy J., Hanewinkel M. (2006): A forest management risk insurance model and its application to coniferous stands in southwest Germany. Forest Policy and Economics, ***8***: 161–174.

Hosmer D.W., Lemeshow S. (2000): Applied Logistic Regression. 2nd Ed. New York, John Wiley & Sons, Inc.: 392.

Jakuš R. (1998): Types of bark beetle (Coleoptera, Scolytidae) infestation in spruce forest stands affected by air pollution, bark beetle outbreak and honey fungus (*Armillaria mellea*). Anzeiger für Schadlingskunde, Pflantzenschutz, Umweltschutz, ***73***: 41–49.

Jalkanen A., Manttila U. (2000): Logistic regression models for wind and snow damage in Northern Finland based on the National Forest Inventory data. Forest Ecology and Management, ***135***: 315–330.

Kouba J. (1989): Theory of normal forest following random processes, probability of salvage cuttings, and forest production. Lesnictví, ***36***: 925–944. (in Czech)

Konôpka J., Konôpka B., Raši R., Nikolov Ch. (2008): Dangerous directions of winds in Slovakia. Lesnícke štúdie 60, NLC-LVÚ Zvolen: 81. (in Slovak)

Kulla L., Hlásny T. (2008): Multi factorial hazard assessment as a support for conversion priority rating in declining spruce forests. Lesnícky časopis – Forestry Journal, ***54***: 43–52.

Meloun M., Militký J., Hill M. (2005): PC-Based Analysis of Multidimensional Data in Excercises. Praha, Academia: 449. (in Czech)

Nopp U., Netherer S., Eckmüllner O., Führer E. (2001): Parameters for the assessment of the predisposition of Spruce-dominated forests to various disturbing factors with special regard to 8-toothed Spruce bark beetle (*Ips typographus* L.). In: Franc A., Laroussinie O., Karjalainen T. (eds): Criteria and indicators for sustainable forest management at the forest management unit level. EFI Proceedings, ***38***: 99–108.

Schmoldt D.L. (2001): Application of artificial intelligence to risk analysis for forest ecosystems. In: Gadow K.V. (ed.): Managing Forest Ecosystems 2: Risk Analysis in Forest Management. Dordrecht/Boston/London, Kluwer Academic Publishers: 49–74.

Suzuki T. (1971): Forest Transition as a Stochastic Process. Wien, Mitteilungen der Forstlichen Bundesversuchsanstalt (FBVA), Heft 91: 137–150.

Valinger E., Fridman J. (1999): Models to asses the risk of snow and wind damage in pine, spruce and birch forests in Sweden. Environmental Management, ***24***: 209–217.

Zlatník A. (1976): Forest Phytocenology. Praha, SZN: 495. (in Czech)

Received for publication March 30, 2010

Accepted after corrections October 26, 2010

Corresponding author

Ing. Ladislav Kulla, PhD., National Forest Centre, Forest Research Institute Zvolen,
T. G. Masaryka 22, 960 92 Zvolen, Slovakia
e-mail: kulla@nlcsk.org